UNIVERSIDAD COMPLUTENSE DE MADRID
FACULTAD DE PSICOLOGÍA



TESIS DOCTORAL

Concepción, desarrollo y validación de un modelo interaccionista de competencias profesionales en la industria 4.0

Design, development and validation of an interactionist model of professional competencies for industry 4.0

MEMORIA PARA OPTAR AL GRADO DE DOCTOR

PRESENTADA POR

Marco Edinson Peña Jimenez

Directores

Adalgisa Battistelli
Mirko Antino

Madrid

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THÈSE EN COTUTELLE PRÉSENTÉE

POUR OBTENIR LE GRADE DE

DOCTEUR DE

L'UNIVERSITÉ DE BORDEAUX

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SPÉCIALITÉ : Psychologie

Par **Marco Edinson PEÑA JIMENEZ**

CONCEPTION, DEVELOPPEMENT ET VALIDATION D'UN MODELE INTERACTIONNISTE DES COMPETENCES PROFESSIONNELLES POUR L'INDUSTRIE 4.0

DESIGN, DEVELOPMENT AND VALIDATION OF AN INTERACTIONIST MODEL OF PROFESSIONAL COMPETENCIES FOR INDUSTRY 4.0

Sous la direction de Adalgisa BATTISTELLI et Mirko ANTINO

Soutenue le 17 décembre 2021

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Mme BATTISTELLI, Adalgisa	Professeure	Université de Bordeaux	Directrice
M. ANTINO, Mirko	Professeur	Universidad Complutense de Madrid	Directeur

I dedicate this work to my family and,
in particular to my beloved mother.
Thank you for encouraging me to fulfill my dreams.

I dedicate this work to my professional
and personal mentors. Without you,
this dream would not have come a reality.

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Title: Design, development and validation of an interactionist model of professional competencies for industry 4.0

Abstract

New technologies (e.g., artificial intelligence, big data, cloud computing, collaborative robots, drones) are currently shaping a new world of work and organizations, also known as "Industry 4.0". In this context, research on skills has become crucial to prepare individuals for the challenges of this emerging industry. Although many efforts have been made to identify critical skills (e.g., digital, technical) to meet the immediate and specific demands of companies and the labor market, the study of skills supporting human agency to cope with changing and complex contexts is still limited.

Based on the agentic approach of social cognitive theory, this research aims to identify and evaluate skills allowing individuals to manage and transform their environment through the design and implementation of strategies.

First, we conducted a systematic literature review to identify the different skills associated with Industry 4.0, which allowed us to identify five major skills clusters (i.e., cognitive, interpersonal/managing people, functional business, technological, strategic). Second, we carried out a study to explore skill requirements by those already working in a high-tech company in the aerospace industry as well as possible differences related to the organizational role. The results showed that cognitive, functional business, managing people and strategic skills are considered essential capacities to cope with the their organizational demands, which differ at the organizational level (i.e., managers, subordinates). Third, the theoretical bases and a measure were developed to assess different "strategic" skills (i.e., anticipating, scanning, connecting, goal setting, planning, monitoring, enacting) enabling individuals the design and implementation of strategies which were examined through a study aimed at evaluating the psychometric qualities of such questionnaire. The results confirmed

that the French version of the strategic skills questionnaire demonstrated satisfactory psychometric properties in the sample of employees studied. Finally, we examined the relationship between strategic capacities (in the form of two higher-order strategic capacities) and proactive performance through the mediating role of self-efficacy. The results revealed that there are two higher-order strategic capacities (i.e., situational assessment, strategy implementation), shaping seven different but related lower-order strategic skills (i.e., anticipating, scanning, connecting, goal setting, planning, monitoring, enacting). Likewise, while the relationship between situational assessment capacity and proactive performance is partially mediated by self-efficacy, the relationship between strategy implementation capacity and proactive performance is fully mediated by self-efficacy.

Taken together, these results provide preliminary empirical evidence on the potential that strategic skills have to develop human agency through the design and implementation of strategies, as a way of facing the challenges of Industry 4.0, which are discussed in terms of their theoretical, methodological and practical implications.

Keywords: Competency, Skills, Technology, Industry 4.0

Titre: **Conception, développement et validation d'un modèle interactionniste des compétences professionnelles pour l'industrie 4.0**

Résumé

De nouvelles technologies (p.ex., big data, cloud computing, drones, intelligence artificielle, robots collaboratifs) sont actuellement en train de façonner un nouveau monde du travail et des organisations, aussi connu comme « Industrie 4.0 ». Dans ce contexte, la recherche sur les compétences professionnelles est devenue essentielle pour préparer les individus aux défis de cette industrie émergente. Bien que de nombreux efforts aient été déployés afin d'identifier des capacités critiques (p.ex., digitales, techniques) pour satisfaire la demande immédiate et spécifique des organisations et du marché du travail, l'étude des capacités favorisant l'agentivité humaine pour faire face aux contextes changeants et complexes est encore limitée.

Sur la base de l'approche agentique de la théorie sociocognitive, cette recherche vise à identifier et évaluer des capacités permettant aux individus de gérer et transformer leur environnement à travers le design et mise en œuvre des stratégies.

En premier lieu, nous avons mené une revue systématique de la littérature afin d'identifier les différentes capacités professionnelles associées à l'industrie 4.0, permettant identifier au moins cinq grands types de capacités (c.-à-d., cognitives, interpersonnelles/gestion des personnes, fonctionnelles, technologiques, stratégiques). En deuxième lieu, nous avons fait une étude dans le but d'explorer les capacités demandées par ceux qui travaillent déjà dans une entreprise hautement technologique du secteur aérospatial ainsi que les possibles différences par rapport au niveau organisationnel. Les résultats ont montré que les capacités cognitives, fonctionnelles, gestion de personnes et stratégiques sont considérées comme essentielles pour faire face aux exigences de leur organisation, lesquelles différent vis-à-vis le niveau organisationnel (c.-à-d., managers, subordonnés). En troisième lieu, il a été développé les bases

théoriques et une mesure pour évaluer de différentes capacités « stratégiques » (c.-à-d., anticiper, analyser, connecter, fixer des objectifs, planifier, surveiller, agir) permettant aux individus l'élaboration et la mise en œuvre des stratégies lesquelles ont été examinées à travers une étude ayant pour objectif l'évaluation des qualités psychométriques du questionnaire. Les résultats ont permis d'attester que la version française du questionnaire des capacités stratégiques fait preuve des propriétés psychométriques satisfaisantes dans l'échantillon de travailleurs analysé. Enfin, nous avons examiné le lien entre les capacités stratégiques (sous la forme de deux supra-capacités stratégiques d'ordre supérieur) et la performance proactive à travers le rôle médiateur de l'auto-efficacité. Les résultats suggèrent qu'il y a deux supra-capacités stratégiques d'ordre supérieur (c.-à-d., évaluation de la situation, mise en œuvre de la stratégie), façonnant sept différentes, mais associées capacités stratégiques d'ordre inférieur (c.-à-d., anticiper, analyser, connecter, fixer des objectifs, planifier, surveiller, agir). De plus, alors que la relation capacité d'évaluation de la situation – performance proactive est partiellement médiée par l'auto-efficacité, la relation entre la capacité de mise en œuvre de la stratégie et la performance proactive est entièrement médiée par l'auto-efficacité.

Globalement, ces résultats apportent évidence empirique préliminaire sur le potentiel que les capacités stratégiques ont pour développer l'agentivité humaine à travers le développement et implémentation des stratégies, comme une façon de faire face aux challenges de l'industrie 4.0, lesquelles sont discutées en termes de leurs implications théoriques, méthodologiques et pratiques.

Mots clés: Compétence, Capacités, Technologie, Industrie 4.0

Título: Concepción, desarrollo y validación de un modelo interaccionista de competencias profesionales en la industria 4.0

Resumen

Las nuevas tecnologías (v.g., inteligencia artificial, big data, computación en la nube, robots colaborativos, drones) están actualmente dando forma a un nuevo mundo del trabajo y las organizaciones, también conocido como "Industria 4.0". En este contexto, la investigación sobre competencias se ha vuelto crucial para preparar a las personas para los desafíos de esta industria emergente. Aunque se han realizado muchos esfuerzos para identificar habilidades críticas (v.g., digitales, técnicas) para satisfacer las demandas inmediatas y específicas de las empresas y el mercado laboral, el estudio de las habilidades que apoyan la agencia humana para hacer frente a contextos cambiantes y complejos es aún limitado.

Con base en el enfoque de agencia humana de la teoría social cognitiva, esta investigación se plantea como objetivo identificar y evaluar habilidades que permitan a los individuos gestionar y transformar su entorno a través del diseño e implementación de estrategias.

En primer lugar, realizamos una revisión sistemática de la literatura para identificar las diferentes habilidades asociadas con la Industria 4.0, lo que nos permitió identificar cinco grupos de habilidades principales (i.e., cognitivas, interpersonales / gestión de personas, funcional para el negocio, tecnológicas, estratégicas). En segundo lugar, llevamos a cabo un estudio para explorar las habilidades requeridas por quienes ya trabajaban en una empresa altamente tecnológica en la industria aeroespacial, así como las posibles diferencias relacionadas con el rol en la organización. Los resultados mostraron que las habilidades cognitivas, funcionales para el negocio, de gestión de personas y estratégicas se consideran capacidades esenciales para hacer frente a las demandas organizacionales, las cuales difieren a nivel del rol en la empresa (i.e., gerentes, subordinados). En tercer lugar, se desarrollaron las

bases teóricas y una medida para evaluar diferentes habilidades “estratégicas” (i.e., anticipar, escanear, conectar, establecer metas, planificar, monitorear, ejecutar) que permitan a las personas el diseño e implementación de estrategias que fueron examinadas a través de un estudio enfocado en la evaluación de las propiedades psicométricas de dicho cuestionario. Los resultados confirmaron que la versión francesa del cuestionario de habilidades estratégicas demostró propiedades psicométricas satisfactorias en la muestra de empleados estudiados. Finalmente, examinamos la relación entre las habilidades estratégicas (en forma de dos capacidades estratégicas de orden superior) y el desempeño laboral proactivo a través del papel mediador de la autoeficacia. Los resultados revelaron que existen dos capacidades estratégicas de orden superior (i.e., evaluación de la situación, implementación de la estrategia), que dan forma a siete habilidades estratégicas de orden inferior diferentes pero relacionadas (i.e., anticipar, escanear, conectar, establecer metas, planificar, monitorear, ejecutar). Asimismo, mientras que la relación entre la capacidad de evaluación situacional y el desempeño proactivo está parcialmente mediada por la autoeficacia, la relación entre la capacidad de implementación de la estrategia y el desempeño proactivo está totalmente mediada por la autoeficacia.

En conjunto, estos resultados aportan evidencia empírica preliminar sobre el potencial que tienen las habilidades estratégicas para desarrollar la agencia humana a través del diseño e implementación de estrategias, como una forma de enfrentar los desafíos de la Industria 4.0, los cuales se discuten en términos de sus aspectos teóricos, metodológicos e implicaciones prácticas.

Palabras clave: Competencia, Capacidades, Tecnología, Industria 4.0

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Texte long Français

Introduction

Un ensemble de nouvelles technologies intelligentes et interconnectées (e.g., intelligence artificielle, big data, robots collaboratifs, cloud computing, drones, réalité virtuelle) sont en train de bouleverser les fondements de la société, y compris le monde du travail et des organisations (e.g., le marché du travail, les formes de emploi, les perspectives de carrière, l'environnement de travail, les missions du poste) (Landers et Marin, 2021; Langer et Landers, 2021). En plein essor, ce nouveau monde du travail, aussi connu comme « Industrie 4.0 » ou la « Quatrième révolution industrielle », est en train de transformer non seulement la façon dont nous travaillons, mais aussi la façon dont nous interagissons avec nos collègues au travail (Battistelli & Odoardi , 2018, Cascio & Montealegre, 2016).

D'ici 2030, par exemple, certaines estimations suggèrent qu'environ 8,5 % de la main-d'œuvre mondiale (environ 20 millions d'emplois) pourrait être amené vers d'autres métiers ou tâches par cette révolution technologique, et plus particulièrement par le développement de l'automatisation et de la robotique (Oxford Economics, 2019). D'autres auteurs considèrent qu'environ 75 à 375 millions de personnes pourraient avoir besoin de changer d'emploi (y compris de métiers) (Manyika et al., 2017). En tout cas, au-delà de ces chiffres, ce panorama montre l'importance de préparer les employés pour faire face aux challenges actuels et futurs de cette nouvelle révolution industrielle (Ackerman & Kanfer, 2020).

Dans ce contexte, l'objectif général de cette thèse est de proposer et d'évaluer un cadre de compétences permettant aux individus de développer leurs capacités d'élaboration et d'implémentation de stratégies (de l'évaluation de la situation à la mise en œuvre de la stratégie) comme un moyen de surmonter les défis de l'industrie 4.0. Pour ce faire, en s'appuyant sur l'approche de l'agentivité humaine de la Théorie Sociocognitive (Bandura, 2006, 2018) et des modèles d'action-régulation (Gollwitzer, 2018 ; Roe, 1999a), cette recherche fait face au défi

de développer un modèle des compétences stratégiques à l'ère du numérique. Tout cela à travers une vision globale des compétences liées à l'industrie 4.0, une étude exploratoire dans une entreprise représentative de l'industrie 4.0, le développement du cadre conceptuel et une mesure des compétences stratégiques, et l'évaluation de certains des corrélats des compétences stratégiques.

Le présent document est organisé en cinq chapitres. Les quatre premiers chapitres abordent notre objectif de recherche, tandis que le cinquième chapitre fournit une discussion générale de la recherche doctorale.

Chapitre 1. Compétences dans l'industrie 4.0 : Une revue systématique de la littérature

Le premier chapitre présente un état de l'art sur les capacités liées à l'industrie 4.0 à travers une revue systématique de la littérature (de 2011 à 2020), ainsi qu'un cadre intégral de compétences basé sur les résultats de cette revue de littérature. En fait, il existe aujourd'hui différents cadres ou modèles de compétences conçus – comme ressources isolées – pour répondre à des défis sociétaux ou professionnels spécifiques (e.g., techniques, organisationnels, industriels). Toutefois, l'intégration et l'étude de ces compétences – comme ressources intégrées – devient essentielle pour analyser la capacité fonctionnelle ou le rôle de ces compétences dans son ensemble. C'est pour cette raison que nous avons développé un cadre de compétences « Human Agency » intégrant les compétences en termes de capacités fonctionnelles intégrées.

Dans ce chapitre est également présentée une définition alternative de « l'industrie 4.0 » représentant notre vision théorique – sous l'angle de la psychologie organisationnelle – de cette industrie émergente, qui diffère de nombreuses définitions se focalisant sur le côté technologique ou industriel de ce nouveau monde du travail. Ces résultats et ce cadre conceptuel fournissent à la fois aux chercheurs et aux praticiens organisationnels un aperçu général pour évaluer les lacunes en matière de compétences, mais également pour le processus de

d’actualisation et de perfectionnement professionnel, devenant ainsi le cadre macro et théorique des compétences qui façonnent notre recherche doctorale.

Chapitre 2. Compétences requises dans l'industrie 4.0 : Une étude exploratoire

Le deuxième chapitre présente les résultats d'une étude empirique explorant les compétences requises (à deux moments différents) des employés travaillant pour une entreprise hautement technologique du secteur aéronautique (Burrus et al., 2013 ; Peterson et al. ., 2001). Tandis que certaines études (e.g., Sousa & Wilks, 2018 ; Van Laar et al., 2018) se sont concentrées sur l'exploration des compétences pour des étudiants, des consultants ou encore des cadres d’entreprise, notre travail propose plutôt d’investiguer les compétences requises par les travailleurs qui connaissent déjà cette transformation technologique. Cela nous semble particulièrement important non seulement pour mieux comprendre la perception des employés sur les capacités requises pour effectuer leur travail de manière appropriée dans une entreprise industrie 4.0, mais aussi parce que cela fournit des évidences empiriques complétant d'autres approches (e.g., centrée sur l’organisation ou sur le métier).

Pris ensemble, ces résultats suggèrent que des groupes de compétences différents et connexes représentent un atout personnel pour faire face aux exigences organisationnelles de l'industrie 4.0, lesquels peuvent varier en fonction du rôle dans l’organisation et au fil du temps. Cette étude nous a permis de vérifier, à travers une évaluation empirique et concrète de l'industrie 4.0, différentes dimensions du cadre de compétences de l'agentivité humaine présentées dans le chapitre précédent. De cette manière, on contribue à mettre en évidence les compétences requises par les personnes qui expérimentent ce nouvel environnement de travail dans leur activités de travail quotidiennes.

Chapitre 3. Compétences stratégiques : Développement théorique et d’une mesure

S'inspirant de l'approche agentique de la théorie sociocognitive (Bandura, 2006, 2018), le chapitre 3 se concentre sur l'étude des compétences stratégiques, un ensemble de

compétences soutenant le processus d'élaboration de la stratégie (de l'évaluation de la situation à la mise en œuvre de la stratégie) comme un moyen d'exercer « contrôle » dans un environnement de travail de plus en plus changeant et interconnecté. Sur la base des résultats de la revue de la littérature (chapitre 1) et de l'étude exploratoire (chapitre 2), nous considérons que les compétences stratégiques représentent un atout personnel précieux pour favoriser le développement de l'agentivité humaine au travail, à travers l'évaluation environnementale du travail et la conception et mise en œuvre de stratégies.

Alors que de nombreux cadres de compétences se sont concentrés sur une liste de compétences dont les organisations ou les marchés du travail ont besoin (e.g., compétences numériques, programming), ce travail examine plutôt des compétences permettant aux individus de développer leur capacité, non seulement à s'adapter, mais aussi à transformer de manière proactive leur environnement de travail grâce à des capacités pour élaborer de stratégies. En utilisant des modèles théoriques d'action-régulation (Modèle Rubicon : Gollwitzer, 2018 ; Modèle Calendrier : Roe, 1999a), qui sont cohérents avec l'approche de l'agentivité humaine (Bandura, 2018 ; Kanfer et al., 2017), cette section fournit les fondements conceptuels des compétences stratégiques (c.-à-d. anticiper, scanner, connecter, établir des objectifs, planifier, surveiller, agir) et propose une nouvelle mesure pour évaluer telles compétences. Ce chapitre met en évidence les qualités psychométriques satisfaisantes du questionnaire sur les compétences stratégiques, ce qui nous permet d'avoir un outil pour approfondir la recherche sur les compétences stratégiques et leur relation avec d'autres comportements organisationnels.

Chapitre 4. Corrélats des compétences stratégiques : Relation entre les compétences stratégiques, l'auto-efficacité et la proactivité des tâches individuelles

Le quatrième chapitre examine la relation entre les compétences stratégiques, l'auto-efficacité et les comportements proactifs au travail à travers une étude s'efforçant de

comprendre comment les compétences stratégiques sont façonnées par des capacités stratégiques d'ordre supérieur liées à l'auto-efficacité et la performance au travail.

Des nombreuses recherches sur la capacité mentale générale (e.g., McGrew, 2009), et plus spécifiquement sur la capacité au travail (e.g., Brady et al., 2020), suggèrent que la capacité à résoudre des problèmes complexes peut s'expliquer par au moins trois formes (ou niveaux hiérarchiques) de capacités cognitives, également appelées « strates » (McGrew, 2009). Sur la base de ce postulat théorique, nous explorons dans ce chapitre l'existence de deux compétences stratégiques d'ordre supérieur (c.-à-d. l'évaluation de la situation, la mise en œuvre de la stratégie) façonnant des compétences stratégiques d'ordre inférieur (c.-à-d. anticiper, scanner, connecter, établir des objectifs, planifier, surveiller, agir). Également, nous avons évalué le rôle de l'auto-efficacité (qui est considérée comme un mécanisme central de l'agentivité humaine), en tant que médiateur de la relation entre les capacités stratégiques d'ordre supérieur et la performance proactive au travail. Dans son ensemble, ce travail représente, d'un côté, une première mais essentielle étape pour mieux comprendre la nature et la forme des compétences stratégiques. D'un autre côté, cette étude met aussi en avant le potentiel des compétences stratégiques pour surmonter les défis d'un monde du travail de plus en plus changeant, complexe et numérique.

Chapitre 5. Discussion générale

Sur la base des résultats des chapitres précédents, le cinquième chapitre présente une discussion générale concernant les implications théoriques, méthodologiques et pratiques de cette recherche doctorale. Même si chaque étude fournit sa propre discussion, nous élargissons notre analyse en explorant le rôle de l'agentivité humaine dans un environnement de travail de plus en plus numérique, changeant et complexe. De plus, nous présentons les forces et les limites de l'ensemble de la thèse qui doivent également être prises en compte pour analyser de manière appropriée les résultats actuels, les contributions de la recherche et les pistes de

recherche potentielles pour élargir ainsi nos connaissances sur la nature, la forme et la dynamique des compétences stratégiques, mais aussi sur la manière dont celles-ci agissent ensemble pour faire face aux défis et aux exigences organisationnelles à l'ère numérique.

Conclusion

La recherche sur les compétences professionnelles est devenue essentielle pour relever les défis organisationnels de cette nouvelle révolution industrielle. S'appuyant sur l'approche de l'agentivité humaine, cette recherche aborde le défi d'explorer, de développer et d'évaluer un cadre de compétences stratégiques, ou un ensemble de capacités d'élaboration et implémentation des stratégies permettant aux individus de gérer et de transformer activement leur environnement. Dans son ensemble, notre revue théorique et nos études empiriques fournissent non seulement une vue globale des compétences liées à l'industrie 4.0, mais également les fondements théoriques et les évidences empiriques préliminaires sur la nature, la forme et la valeur organisationnelle des compétences stratégiques à l'ère du numérique.

General Introduction

A new set of smart technologies (e.g., artificial intelligence, big data, collaborative robots, cloud computing, drones, virtual reality) is shaking the foundations of society, and especially, the world of work and organizations (e.g., labor market, forms of employment, career prospects, workplace environment, job design) (Landers & Marin, 2021; Langer & Landers, 2021). This emerging and booming new world of work, also known as 'Industry 4.0' or 'Fourth Industrial Revolution', is already triggering substantial changes not only in the way we work, but also in how we interact with others at work (Battistelli & Odoardi, 2018; Cascio & Montealegre, 2016). By 2030, for instance, some estimates suggested that approximately 8.5% of the global workforce (roughly 20 million jobs) might be displaced by the current technological revolution, and more specifically by automation and robotics development (Oxford Economics, 2019), while others consider that approximately 75 to 375 million people may need to change their jobs (including occupational categories) and therefore they will need to learn and develop new skills (Manyika et al., 2017).

As if this were not enough, the global COVID-19 pandemic pushed many organizations of all types and sizes from all over the world to rapidly (and sometimes unexpectedly) adopt new technologies to ensure their core business operations but also to explore new opportunities for growth and competitiveness (Lund et al., 2021). According to preliminary reports (e.g., McKinsey Global Survey of Executives, see McKinsey & Company, 2020), indeed, pandemic forced businesses from all over the world to partially or completely digitize their products and/or services by 55%, and produced an acceleration of technology adoption of about 7 years in comparison to previous years (2017-2019) (c.f., Asia-Pacific: 54% of digitization and more than 10 years of acceleration; Europe: 50% of digitization and 7 years of acceleration; North America: 60% of digitization and 6 years of acceleration). In any case, given this panorama, many labor stakeholders (e.g., employers, governments, unions) agree that one of the most

important industry4.0 challenges is developing a well-prepared workforce to ensure a successful and sustainable technological transformation, thus making skill research relevant to pave the way for this emerging industry (e.g., Ackerman & Kanfer, 2020; Scully-Russ & Torraco, 2020; World Economic Forum, 2020).

An example which illustrates the importance of skill research in the digital age can be found in the aeronautics sector. The aviation subsidiary of General Electric (2017) adapted smart glasses and then connected them to a central server to improve the building process of jet engines. As a result, employees using these wearables could receive digitized instructions (e.g. technical procedures, video tutorials) during the assembling process of jet engine, and even using an integrated voice command function to contact technical experts for real-time assistance (e.g. by using live video connection), thus reducing the production errors but also increased the company's productivity and efficiency. As it was expected, employees needed to be trained to use these new wearable computer glasses but also to deal with different changes at work (e.g., job-related tasks and duties, relationship with others, human-technology interaction). With that in mind, and beyond the skills required to use a specific type of technology, which are the skills people require to become strategic problem solvers and decision makers able to benefit from a more changing digital and smart work environment?

Over the past years, literature review on skill research has revealed that significant steps have been taken to identify and evaluate skills required to face the current social and labor challenges, in particular for industry 4.0 (for a comprehensive review see Chaka, 2020; Kipper et al., 2021; van Laar et al., 2020). For instance, by following an organization-centered approach, some (e.g., Dierdorff & Elligton, 2019; van Laar et al., 2018) have contributed to the identification and assessment of various skills (e.g., digital, programming, data analysis) that are currently needed to master specific technologies, immediate labor demands or emerging market trends. Nonetheless, further research based on a human-centered approach is needed to

uncover the potential some skills (e.g., anticipating, scanning, goal setting, planning) may have to develop the human agency at work (e.g., Bandura, 2018; Cenciotti et al., 2020; Hirst et al., 2020, Peña-Jimenez et al., 2021). In this regard, instead of drawing our attention to identify or develop skills to manage new technological tools that can rapidly evolve (or even become obsolete), the current doctoral research focused on those skills allowing people to actively regulate their actions and transform their environment as a way to cope with the challenges of this increasingly digital changing and complex world of work.

Before presenting our research goal and the organization of the present work, and even though the reader will have a broader review of "skills" and "industry 4.0" throughout the document, we briefly present our theoretical view on these two key aspects that shape this doctoral research.

The complexity of the concept of competency: Toward a conceptual distinction

Etymologically, the word 'competency' comes from the Latin word 'competentia' which means "is authorized to judge" or "has the right to speak". Indeed, competency has been largely studied by different disciplines, take economy, education, human resources, law, management, psychology, sociology, for instance. Nevertheless, in terms of scientific literature, competency is considered a complex and fuzzy concept whose meaning remains unclear, which is interchangeably used as skill, ability, capacity, expertise and even intelligence (Garavan & McGuire, 2001; Le Deist & Winterton, 2005; Mulder, 2014). Within the organizational and higher-education context, there are many other alternative forms of the term competency as if it were the same concept, take, "competence" and "competencies" for instance.

Thus, regarding this theoretical discussion, Mulder (2014) claims that "competence" is a set of competencies whereas "competency" is a useful cluster of skills, knowledge and attitudes to performance-related environment. Likewise, Kurz and Bartram (2002) consider that "competencies" are behavioral repertoires while "competence" is presented as a state of

achievement. This shows us that making a clear distinction of all these concepts is not an easy endeavor, especially due to its widespread use by organizational scholars and practitioners. Thus, to clarify the conceptual boundaries between competency and other related concepts, we present below a short definition of different but related personal resources and attributes.

Considering that these personal factors are almost always present not only in academia but also in everyday language of organizational behavior and human resources practitioners, there is a need for clarifying these elementary notions associated to competency such as skills, knowledge, abilities and other resources (KSAO). Thus, according to many KSAO scholars (Campion et al., 2011; El Asame & Wakrim, 2018), *Knowledge* refers to the information system which is necessary to perform assigned tasks, duties, and roles. For instance, we can distinguish information about theories, methods, procedures, rules, functions, tools, etc. *Skills* represent everything that a person is capable of doing as a whole in a given organizational setting, such as problem analysis, team collaboration, leadership. *Ability* is considered as the capacity to perform a physical or mental act which is commonly associated with an innate characteristic, for example, analytical reasoning, verbal fluency, distributed attention. *Other characteristics* refer to a set of personality traits, meaningful experiences and attitudes that distinguish an individual, such as openness, conscientiousness, interests, and values.

To illustrate these different concepts let us take, for example, the case of a software engineer. A competent engineer is someone who is capable of developing an application, software or another digital system adapted to an organizational setting, and to do this, this professional will need an information background or knowledge on, for example, network systems theory, international standards to develop software, programming languages and protocols, etc. Furthermore, one may need skills of computer coding, software development, technological assessment, etc. In terms of abilities, it can be useful abstract thinking, analytical reasoning, written communication, etc.

In scientific literature, competency has been defined as the personal ability or skills learned through different learning experiences and previous work experiences which allow individuals to effectively perform a task or duty (El Asame & Wakrim, 2018; Roe, 2002). Based on this premise, two central elements of discussion emerge from such definition: first, one of the most important behavioral indicators of competency is our performance at work (e.g., task, contextual, adaptive, proactive performance); second, skills would be a core element which is developed by different learning experiences - within and outside the organization (El Asame & Wakrim, 2018; Roe, 2002). This implies that skills are an essential asset for a high-level job performance (Roe, 1999a, DeNisi & Murphy, 2017), but also that skills are learned, mobilized, modeled, and adapted to the circumscribed environment, which means that the organizational environment has a critical role to foster (or limit) the skill acquisition and development and many other valuable behaviors at work (Evers & Van der Heijden, 2017; Parker & Grote, 2020).

Therefore, as a way to clarify our theoretical view regarding competency, in the present doctoral work, we adhere to the definition proposing competency as *"a complex articulation of knowledge, skills, attitudes, self-images and motivations which, in interaction with one's surroundings, is constantly being constructed, allowing the individual to implement appropriate behaviors to the demands of work and in a harmonious relationship that can give the individual a feeling of adequacy"* (Battistelli, 1996, p. 240).

Based on this theoretical view of competency (Battistelli, 1996, El Asame & Wakrim, 2018; Roe, 2002), in the current work, we focus on skills instead of other personal resources (e.g., knowledge, abilities, attitudes) allowing individuals to overcome challenges at work for three reasons. First, skills are considered essential components of professional competency or proficiency in a given context (e.g., educational, organizational), which allows us to focus on a fundamental constituent of competency at work (Campion et al., 2011; El Asame & Wakrim, 2018). Second, skills are defined as malleable and dynamic capacities evoking metaprocesses

that can be applied within the range of analogous events, situations or tasks, in comparison with other personal assets (e.g., traits, knowledge) considered as more stable, innate or cumulative characteristics (El Asame & Wakrim, 2018; Roe, 2002). Last, though we acknowledge that there are many other personal resources (e.g., knowledge, motives, traits) explaining proficiency at work, skills are seen as a set of integrated and interactional resources used to solve complex problems which implies a certain degree of knowledge that is used to cope with the challenging situation or to achieve a goal (El Asame & Wakrim, 2018; Roe, 2002). Therefore, skills are defined and evaluated here as the core element of competency at work, thus becoming the central unit of analysis of the entire doctoral research.

The human agency approach: An interactionist and proactive view of human action

People are nowadays facing many complex and rapid changes because of the emergence and introduction of smart technologies within the world of work and organizations (Cascio & Montealegre, 2016; Landers & Marin, 2021). While some consider that humans are passive agents whose behavior is shaped by their immediate context (e.g., technological work environment), others conceive humans as actors who seek to transform their environment in active and engaged way (Bandura, 2006, 2018). In other words, people intentionally pursue a goal or deal with a challenging situation to change their life's courses or to build a better future, a central postulate of the conception of human agency (Bandura, 2018, 2019).

Human agency is defined as the individuals' capacity to exercise control over their surrounding environment, and an essential or symbolic capacity allowing people's adaptation and renewal over time (Bandura, 2006, 2018). According to the Social Cognitive Theory (SCT, Bandura, 2001, 2018), this human agency is supported through three distinctive properties: *forethought* which refers to develop a depiction of an expected future as a motivator of human action, *self-reflectiveness* which represents the general evaluation on the meaning of pursuing a goal, the individual's *efficacy* and potential consequences of undertaking a task, and *self-*

reactiveness which evokes the efforts to execute actions plans oriented to attain goals. Likewise, unlike other non-mechanistic theories of human action, SCT (Bandura, 2006, 2018) states that human functioning is the result of a triadic codetermination or interplay of behavioral, environmental and personal determinants, but equally, the people's capacity to deal with a problem is not the mere sum of capacities but rather a set of integrated and dynamic resources.

Grounded on the agentic approach of the SCT (Bandura, 1986, 2006, 2018), and action-regulation frameworks (Gollwitzer, 2018; Roe, 1999a), the present thesis makes a review and evaluation of a skill set developing the human agency through strategy-making process capacities. As will be presented more extensively throughout the thesis, this doctoral research postulates that developing skills allowing individuals to make an appropriate situational assessment as well as to design and implement effective strategies becomes essential for preparing the workforce to actively manage and transform industry 4.0 challenges into an opportunity. By doing so, we seek to pave the way for developing the human capacities for living and working in an era where rapidly evolving technologies are creating and more challenging, changing and world of work and organizations.

Research Goals

General Objective

The overall goal of the present doctoral research was to propose and evaluate a skill framework allowing individuals to develop their strategy-making capacities (from situational assessment to strategy implementation) as a way to overcome the work and organizational challenges of an emerging industry, also known as Industry 4.0. To do so, based on the SCT and action-regulation frameworks, the current research addresses the challenge of exploring the potential strategic skills in the digital age through: a comprehensive view of skills related to the industry 4.0, an exploratory study in a representative company of industry 4.0, the conceptual

and measurement development of strategic skills, and the evaluation of some of the correlates of strategic skills.

Specific Objectives

- **Objective 1:** To conduct a systematic literature review on skills proposed to face the industry 4.0 challenges, to distinguish and group them into an integrated skill framework focused on functional and unified capacities instead of isolated resources.
- **Objective 2:** To explore skill requirements of employees working for a company whose activities and process are driven by cutting-edge technologies, as well as potential differences regarding the organizational role and organizational context.
- **Objective 3:** To provide the conceptual basis of the strategic skills framework and to evaluate the psychometric properties of a new measure which measuring the anticipating, scanning, connecting, goal setting, planning, monitoring and enacting skills supporting the strategy-making process at work (from situational appraisal to strategy implementation).
- **Objective 4:** To examine how the different strategic skills, in the form of two higher-order strategic capacities (i.e., situational appraisal, strategy implementation) are related to individual task proactivity at work through the mediating role of self-efficacy.

Organization of the Doctoral Thesis

The present document is divided into five chapters. The first four chapters address our above-mentioned research goals, while the fifth chapter provides a general discussion. Regarding the information presented in each section, it should be pointed out that in order to facilitate the review and analysis of this work, each chapter integrates their corresponding discussion and references section.

Chapter 1. A Systematic Literature Review on Skills in Industry 4.0

The first chapter presents a state of the art on skills related to industry 4.0 through a systematic literature review (from 2011 to 2020), a study whose focus was to develop a general skill framework based on such findings. Considering that there are nowadays various skill frameworks designed to address specific societal or labor challenges (e.g., technical, organizational, industrial sectors, national strategies), the exploration, identification and classification of these different (and sometimes not so different) skills becomes essential for building an integrated skill framework, focused on functional and complex capacities (rather than isolated skills). In this chapter is also presented an alternative definition of "industry 4.0" representing our theoretical vision – from an organizational psychology angle – of this emerging industry, which differs from many definitions highlighting the technological or industrial side of this new world of work, also known as "Fourth Industrial Revolution".

These findings and conceptual framework provide both organizational scholars and practitioners a general outline to assess skill gaps but equally to upskilling and reskilling process, thus becoming the macro and theoretical skill framework shaping our doctoral research and the following chapters.

Chapter 2. Exploring Skill Requirements for the Industry 4.0

The second chapter presents the results of an empirical study exploring skill requirements (in two different moments) of employees working for a high-technology company from aeronautics sector, by following a worker-centered approach (Burrus et al., 2013; Peterson et al., 2001). While previous studies (e.g., Sousa & Wilks, 2018; Van Laar et al., 2018) have focused on exploring skills considered as necessary by graduate students, consultants or organizational heads, we focus on skills required by employees who are already experiencing these technological changes. This seems particularly relevant not only for better understand the employees' perception about capacities required to appropriately perform their job in a

company industry 4.0, but also because it provides empirical evidence complementing other approaches (e.g., job-oriented, occupational-oriented).

Taken together, these results suggest that different and related skill clusters represent a useful personal asset for dealing with organizational demands of Industry 4.0, which can vary depending on organizational role different and over time. This study allowed us to verify, through an empirical and concrete evaluation of industry 4.0, different theoretical dimensions of the human agency skill framework presented in the previous chapter, thus providing evidence of skills required by people who is experiencing this new work environment in the their daily work activities.

Chapter 3. Strategic Skills: Theoretical and Measurement Development

Drawing from the agentic approach of SCT (Bandura, 2006, 2018), chapter 3 focuses on the study of strategic skills, a skill set supporting the strategy-making process (from situational appraisal to strategy implementation) as a way to exercise 'control' over an increasingly changing and more interconnected work environment.

Based on the previous findings of the literature review (chapter 1) and exploratory study (chapter 2), we consider that strategic skills can be considered a valuable personal asset to foster the human agency development at work through the work environmental assessment and the design and implementation of strategies to 'industry 4.0' challenges. While many skill frameworks focused on a list of skills that organizations or job markets require (e.g., ICT literacy, programming) to face this new digital world of work (Dierdorff & Elligton, 2019; van Laar et al., 2018), we examine rather skill allowing people to develop their capacity, not only to adapt, but also to proactively transform their work environment through strategy-making process capacities. By using action-regulation frameworks (Rubicon Model: Gollwitzer, 2018; Calendar Model: Roe, 1999a) which are consistent with non-mechanist approach such as the human agency (Bandura, 2018; Kanfer et al., 2017), this section provides the conceptual basis

of different and related strategic skills (i.e., anticipating, scanning, connecting, goal setting, planning, monitoring, enacting) and proposes a new measure to assess such skills.

This section lends empirical evidence of satisfactory psychometric qualities of the strategic skills questionnaire, allowing this to have a tool for expanding research on strategic skills and their relationship with other organizational outcomes.

Chapter 4. Enhancing Human Agency with Strategic Capacities at Work

The fourth chapter examines the relationship between strategic skills, self-efficacy and individual task proactivity at work through a study which lays the foundations for further research exploring how strategic skills are shaped by higher-order strategic capacities that are related to self-efficacy and work performance.

On the one hand, considering that substantive research on general mental ability (e.g., McGrew, 2009), and more specifically work ability studies (e.g., Brady et al., 2020), suggest that the human capacity to solve and deal with complex problems can be explained through at least three forms (or hierarchical levels) of cognitive abilities, also known as 'stratum' (McGrew, 2009), we explore the existence of two higher-order strategic capacities (i.e., situational assessment, strategy implementation) shape lower-order strategic skills (i.e., anticipating, scanning, connecting, goal setting, planning, monitoring, enacting). On the other hand, we evaluated the role of self-efficacy (which is considered a central mechanism of human agency), as a mediator of the relationship between higher-order strategic capacities and proactive work performance. On balance, this work represents a first but essential step to better understand the nature and form of strategic skills as well their potential to foster human agency at work as a way to overcome the challenges of a technology-driven but also increasingly changing and complex world of work and organizations.

Chapter 5. General Discussion

Based on the results from previous sections, the fifth chapter presents a comprehensive discussion regarding the theoretical, methodological, and practical implications of the current doctoral research. Even though each study provides its respective discussion, we expand our analysis by exploring the role of human agency has in a more and more digital, changing and complex work environment. Furthermore, we present the strengths and limitations of the entire doctoral research that should also consider to appropriately analyze the current findings and research contributions. Last, potential research avenues are presented to expand the knowledge about the nature, form and dynamic of the strategic skills, but also how these act together to deal with organizational challenges and requirements in the digital age.

Research Contribution

The present study makes several theoretical, methodological and practical contributions to skill literature, and more specifically, skills fostering human agency at work as a way to overcome the industry 4.0 challenges. These contributions are presented and discussed in each chapter of the document but are succinctly evoked here.

From a theoretical angle, for example, this work provides not only a general view about different skills related to industry as part of our systematic literature review, but also a skill framework which integrates different skills in terms of functional capacities instead of a list of single resources. Likewise, we develop the theoretical foundation of the strategic skill framework, a skill set allowing employees to foster their strategy-making capacities to exert control over their environment, something which is a distinctive characteristic of the human agency. From a methodological perspective, for instance, the present study lends empirical evidence on appropriate psychometric properties of the French version of the strategic skills questionnaire, a new measure whose aim is to assess strategic skills and which was designed to be used in the work and organizational context. Last, from a practical standpoint, among other

things, this work provides a unified skill framework which distinguishes different core, enabling and enhancing capacities that can be transformed into training programs in higher education, vocational training institutions and/or organizations.

Thus, taken as a whole, the current study addresses the challenge of exploring, proposing and evaluating a human-centered skill framework, and more specifically strategic skills, as a way to face the contemporary and forthcoming challenges of a more digital, changing and complex world of work that distinguishes industry 4.0.

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Chapter 1

A Systematic Literature Review on Skills in Industry 4.0

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Chapter 1. A Systematic Literature Review on Skills in Industry 4.0

Abstract

A new generation of smart technologies are shaping a new world of work and organizations, also known as "Industry 4.0". Accordingly, identifying skills required for this emerging industry becomes critical. Nevertheless, the research on skills has been focused mainly on skills for specific technologies, sectors or clusters. This work aims at conducting a systematic review of skills related to Industry 4.0 to identify and classify them into an integrated framework based on an agentic perspective. The results showed a wide range of skills that were grouped into five clusters (i.e., cognitive, functional business, technological, interpersonal/managing people, and strategic) of the proposed human agency skill framework. In this way, this work provides an overview of skills required in the digital age as well as a framework which can serve as a basis for investigating skills as a set of capacities fostering the human agency to cope with a fast-changing work environment.

Keywords: skills, human agency, industry 4.0, digital, systematic literature review

1.1. Introduction

Pepper is a robot able to recognize human emotions and interact with people through conversation and, in fact, more than 2000 organizations all over the world are already using this new generation of social, smart and autonomous robots in sectors such as education, research, finance, healthcare and retail (Pandey & Gelin, 2018). As Pepper, many other kinds of intelligent agents (e.g., robots) have been incorporated across all sectors and industries, thus creating different or/and new ways of performing our work-related activities (Broadbent, 2017). The reality, however, is that robotics is just one branch of a large set of smart, interconnected and more adaptive technologies (e.g., artificial intelligence, big data, 3D printing, cloud computing) that are radically changing the job markets and companies (Cascio & Montealegre, 2016; Oztemel & Gursev, 2020).

There is no doubt that the world of work is in a permanent process of transformation, however, there have been some changes or technological advances that represented a turning point in such a process, thus marking a new industrial age (Ackerman & Kanfer, 2020; Battistelli & Odoardi, 2018). The First Industrial Revolution was characterized by the use of steam power that enabled the transition to new manufacturing processes. The Second was marked by the presence of electric power in the production process. The Third was distinguished by electronics and computing technologies. Nowadays, according to Schwab (2017), we are experiencing the Fourth Industrial Revolution which is characterized by the apparition and introduction of smart and interconnected technologies that are creating a new integrated cyber-physical organizational system, also known as the "Industry 4.0" (henceforth I4.0).

Ready or not, the emergence of this new cyber-physical organization is becoming ever more evident in the world of work. For example, a global survey conducted in a sample of executives showed that the COVID-19 pandemic have significantly accelerated the adoption of

digital and internet-connected technologies in all sectors and regions (e.g., the average share of products/services that are partially or fully digitized are 54% for Asia-Pacific, 50% for Europe and 60% for North America), not as a way to improve efficiency but rather as an essential part of their business operations (McKinsey, 2020). This shows, that the Industry 4.0 model is a growing phenomenon, and several world economic actors estimate that about half of occupations are susceptible to be automated and/or digitized (e.g., Bakhshi, Downing, Osborne, & Schneider, 2017; Frey & Osborne, 2017) and international organizations (e.g., Organisation for Economic Co-operation and Development, 2017; World Economic Forum, 2020).

Within this global transformation, a key question for different social agents is how the workforce will adapt, and what the key human factors will be required to successful in this new work scenario. In other words, to develop a skillful workforce to ready to face the different and/or new organizational challenges and to develop employability (Salas, Kozlowski, & Chen, 2017), what are the key skills that we need to focus on?

This research question is of a high actuality. Several researchers in the field are acknowledging that unskilled workers aware feel threatened of being replaced by smart technologies (e.g., artificial intelligence, robotics, and algorithms) showing deleterious effects on several aspects of daily job (lower levels of organizational commitment and career satisfaction, higher levels of cynicism, depression and turnover intentions (Brougham & Haar, 2018; Bhargava, Bester, & Bolton, 2021). Parallelly, to understand the new requirements and promote adaptation, organizational researchers are trying to offer theoretical and empirical works on what skills seem to be key to effort this transformation.

In this line, much of what we know on skills related to the I4.0 addresses organizational and managerial challenges (e.g., Agostini & Filippini, 2019), relates to specific technologies (e.g., Kipper et al., 2021), explores specific occupations (e.g., Maisiri, Darwish, & van Dyk, 2019) or presents relevant broad clusters (e.g., van Laar, van Deursen, van Dijk, & de Haan,

2020). However, such a fragmented scenario offers a gap that we pretend to fill with this work: an integration of the existing scientific knowledge about the skills required in the I4.0 through a human-centered skill framework (Ackerman & Kanfer, 2020; Bandura, 2018; Kanfer & Blivin, 2019). Accordingly, the purpose of the current work is to produce the state-of-the-art on skills related to the I4.0 as an input to develop a human-centered skill framework.

To reach this goal, we carry out a systematic literature review of the last decade (from 2011 to 2021) in order to a) understand and classify the skills related to the I4.0 and b) propose a synthetic and integrative framework. The structure of the paper is the following: first, we briefly present the theoretical background on I4.0 and the implications for skills. Then, we present the characteristics, strategy and outline of the current systematic review. Last, relevant skills identified from the review are presented and integrated into a framework with a focus on human agency. Overall, we consider that the current work has a twofold contribution: on the one hand, from a theoretical view, we extend not only the knowledge about the skills related to I4.0 but also the integration of such skill into a framework focused on human agency; on the other hand, from a practical side, we provide a skill taxonomy focused on functional capacities - rather than isolated resources - to identify and develop skills in I4.0, to prepare practitioners for the (immediate) future challenges of this new and smart industry.

1.2. Theoretical Background

1.2.1. The Human Factor at the Center of the "Industry 4.0": An Organizational Psychology/Organizational Behavior Perspective

Coined in 2011 at the Hanover Fair, "Industry 4.0" is nowadays a generic term widely used by academia, employers, governments, policy-makers and many other labor stakeholders to refer to a new kind of industry where smart, digital and interconnected technologies transform the organizational system and dynamic, including the work processes, procedures and tasks (Liao, Deschamps, Loures, & Ramos, 2017). However, there is no consensus on what

really is I4.0 (Oztemel & Gursev, 2020). At the beginning, I4.0 ("industrie 4.0" in German) was proposed as a German government strategy to seize the potential of a novel industry that integrates advanced technologies, thus creating new manufacturing capabilities, challenges and opportunities, that is a "Cyber-Physical System" (Kagermann, Wahlster, & Helbig, 2013). Over the last ten years, the meaning of the term I4.0 is not the same because of different but complementing perspectives (Pereira & Romero, 2017; Xu, Xu, & Li, 2018).

From a technological and industrial perspective, I4.0 is a concept used to refer us to a new manufacturing environment where digitization and automation maximize and integrate the value chain capabilities (Oesterreich & Teuteberg, 2016). This can be noticed from the three axes of integration: (1) horizontal integration through value networks (e.g., the integration of information technology systems and processes not only within an organization but also among other organizations), (2) vertical integration and networked manufacturing systems (e.g., the integration of different business units and hierarchical levels of an organization), and (3) end-to-end digital integration of the entire value chain (e.g., a flexible manufacturing system capable of customizing products and optimize performance and costs, supported by a digitally integrated value chain) (Kagermann et al., 2013). Some of the most representative technologies of I4.0 are the industrial internet of things, cloud computing, big data, simulation, augmented reality, additive manufacturing, horizontal and vertical systems integration, autonomous robots, and cybersecurity (Alcácer & Cruz-Machado, 2019). In this line, Weyer and colleagues (2015) state that I4.0 can be understood through three paradigms. First, *smart products* which refers to tools and machines technologically equipped (e.g., sensors, microchips), controlled (e.g., by software, digital architecture) and connected to the network (e.g. central server, internet). Second, *smart machine* describes any autonomous device or object fitted with computing technologies and machine-to-machine architecture (e.g., artificial intelligence, machine

learning). Third, *augmented operator* explains how individuals are currently equipped with supportive technologies to become better decision makers and problem solvers.

Viewed from an OP/OB standpoint, technological processes cannot be dissociated from human processes, since technologies and humans are embedded within a same organizational environment (Cascio & Montealegre, 2016; Landers & Marin, 2021). Even if organizations develop some routines to perform well work-related processes and activities, both human and technologies interact each other, thus creating different forms of conjoined agency (Broadbent, 2017; Murray, Rhymer, & Sirmon, 2020). Unlike traditional technologies (e.g., computers, mobile phones), new technologies (e.g., artificial intelligence, smart robots, virtual reality) are able to handle large amounts of data, operate in an interconnected way and autonomously learn new things which offer humans a wide range of opportunities and capabilities to perform their work-related tasks and duties (Battistelli & Odoardi, 2018). For instance, Murray and colleagues (2020) distinguish different typologies of conjoined (human-technology) agency which are related to assisting technologies (e.g., virtual collaboration devices), arresting technologies (e.g., Blockchain-based smart contracts), augmenting technologies (e.g., structured machine learning) and automating technologies (e.g., unstructured machine learning). As such, to explore the human side of the I4.0 is as necessary as the technological side of the current industrial revolution not only to better understand the I4.0-related organizational phenomena but also to identify and develop the current and future I4.0-related organizational capabilities.

Technology has always been central to OP/OB research since technology has shaped work throughout human history (Cascio & Montealegre, 2016). Organizational scholars have contributed extensively to understand the organizational implications of the human-technology interaction through four different technology integration approaches: (1) tech-as-context (i.e., a surrounding and specific working environment), (2) tech-as-causal (i.e., a exogenous force

affecting human processes), (3) tech-as-instrumental (i.e., an exogenous force whose impact is also evaluated through other psychosocial factors and other relationships of interest), and (4) tech-as-designed (i.e., specific design characteristics to assist and/or develop user capacities) (Landers & Marin, 2021). A few examples of these can be seen in different organizational themes such as personnel selection (e.g., Lievens & Sackett, 2017; Oostrom, Van Der Linden, Born, & Van Der Molen, 2013), work design (e.g., Fréour, Pohl, & Battistelli, 2021; Parker & Grote, 2020) and training and development in the workplace (e.g., Bazine, Battistelli, & Lagabrielle, 2020; Nadolny et al., 2020). I4.0 is therefore not the mere presence of a set of technologies within an organizational system but rather an organizational environment where technological processes are intertwined with human processes.

In accordance with the above, it is therefore necessary to develop a conceptual framework of what represents I4.0 to appropriately identify and analyze the skills necessary to face the Fourth Industrial Revolution challenges. Therefore, based on an OP/OB perspective (Cascio & Montealegre, 2016; Landers & Marin, 2021; Murray et al., 2020), we propose the following definition of this new industry:

"*Industry 4.0 is a smart, digital, flexible and interconnected organizational environment where human and technological processes are reciprocally and permanently shaped at an individual, group and organizational level, thus developing different forms of human-technology synergy (or conjoined agency) which is supported by an emerging generation of assisting, arresting, augmenting and/or automating technologies, but above all, by a skillful workforce. Industry 4.0 is also considered as a cyber-physical organizational system designed and capable to deal with and adapt to a more and more changing, virtual, complex and interconnected world of work*".

1.2.2. Skills in Industry 4.0: Building the Workforce for the Future of Work

We are experiencing a significant change in the nature of work and employment because of the emergence and adoption of a new wave of technologies (Ackerman & Kanfer, 2020; Kanfer & Blivin, 2019). Consequently, building the workforce for the I4.0 requires the identification of skills necessary to face the current and future organizational challenges. Many scholars (e.g., McClelland, 1973; Roe, 2002) have defined skill as an ability or proficiency which is acquired and developed through formal and informal learning experiences, and practice. Skill is also considered as one of the key constituents of competency necessary to appropriate perform our work-related activities and duties (Stevens, 2013; Morgeson, Delaney-Klinger, & Hemimgway, 2005).

Over the past ten years, many efforts have been made to identify the skills required to deal with the current and future societal and work challenges in the 21st century, not only by scholars but also by other labor stakeholders (Kanfer & Blivin, 2019). In fact, many countries and international organizations have explored the skill requirements for occupations, roles and sectors, by using national or international taxonomies and databases. Table 1.1 presents a selected sample of some of the most widely used and representative skill taxonomies in the world which are mainly used to identify specific skill gap or identify new market trends at a macro-level (i.e., national, regional level). For instance, the Future of Jobs Report (World Economic Forum, 2020) suggests that some of the most relevant skills for 2025 are (1) analytical thinking and innovation, (2) active learning and learning strategies, (3) complex problem solving, (4) critical thinking and analysis, (5) creativity, originality and initiative, (6) leadership and social influence, (7) technology use, monitoring and control, (8) technology design and programming, (9) resilience, stress tolerance and flexibility, and (10) reasoning, problem-solving and ideation.

Table 1.1. *Selected Representative Samples of International Skills Frameworks*

Framework	Author	Aim
European Skill/competence Qualification and Occupation (ESCO)	European Commission (2013)	A European Union framework whose focus is to evaluate skills, knowledge, attitudes and values, and knowledge and language which is mainly used as a competency dictionary, and a tool to identify and classify professionals in the European Union labor market. More than 2900 occupations and 13,000 skills are specified in this classification of sills, which is available in 27 languages.
Occupational Information Network (O*NET)	U.S. Department of Labor (2012)	A U.S. taxonomy and source of occupational information based on the O*NET Content Model which evaluate different work descriptors: worker characteristics, worker requirements (which includes skill and knowledge education), experience requirements, occupational requirements, workforce characteristics and occupation-specific information. Almost 1000 occupations in the U.S. labor market are stocked in the O*NET database.
Programme for the International Assessment of Adult Competencies (PIAAC)	Organisation for Economic Co-operation and Development (2018)	PIACC is an OECD's an initiative whose aim is to assess key information-processing skills (i.e., literacy, numeracy, technology rich problem solving) in different languages and cultural backgrounds. More than 40 countries have participated in the Survey of Adult Skills whose results are then used for Policy Decision-Making (e.g., education and training, skill gaps).
The Future of Jobs Report	World Economic Forum (2020)	An international framework developed by the World Economic Forum which evaluates, among other subjects, current and emerging trends of the global labor market. By using an adapted version of the O*NET classification and descriptors, the Future of Jobs Survey evaluates emerging and declining skills. The survey also includes a benchmark section where diverse industries (e.g., Advanced manufacturing, Agricultural Food and Beverages, Digital Communications and Information Technology) and countries (e.g., Argentina, China, France, India, South Africa) profiles are presented.

Note. Some of the these frameworks/reports also use international databases (e.g., ILOstat from the International Labour Organization, UNESCO Institute for Statistics, Education Indicators) to compare or complete their analysis.

OP/OB scholars have also contributed to the identification and evaluation of skills in the industry 4.0 era. Table 1.2 reports the existing reviews on skills frameworks related to the digital age where different and complementary approaches and disciplines provide insightful findings about this issue. While some (e.g., Chaka, 2020; Prifti, Knigge, Kienegger, & Krcmar, 2017) proposed a reviewed version of the Great Competencies Model (Bartram, 2005) by adding/relating new dimensions, others present particular competencies for professions in the industry 4.0 (e.g., Silva, Kovaleski, & Pagani, 2019). Another review focuses on a scientific mapping of skills in I4.0 through a bibliometric analysis where is presented not only key skills and knowledge but also enabling technologies (Kipper et al., 2021). More recently, van Laar et al. (2020) developed the 21st century digital skills framework, and even though this proposition focuses on ICT and digital-related skills, we considered that the skills presented are related to the basic technological aspects (e.g., ICT, internet, computer) of the I4.0.

It should be noted, however, that an integration of the current knowledge about skills related to the I4.0 need to be addressed through a systematic literature review. Thus, the present study seeks to bridge this gap through a review expanding the scope of databases (by including more and different databases not only related to engineering and economics, but also to organizational research), the search period (by extending the search to a 10-year review), and the elements of study (by integrating existing reviews/frameworks). Based on such results, we then classify and develop a skill framework. Accordingly, the aim of this work is to identify and analyze different skills, as well as their integration into a skill taxonomy boosting the human capacity in the digital age through a systematic literature review on skills in the industry 4.0 over the last ten years (from 2011 to 2020).

Table 1.2. *Skill Literature Reviews related to the Industry 4.0*

Author	Focus	Main findings / Framework
Chaka (2020)	Skills, competencies and literacies	The author proposed a reviewed framework of the Great Eight Competencies Model (Bartram, 2005), by including 3 new clusters of competencies (i.e., displaying and demonstrating job-related skills/competencies, mastering and displaying language-specific skills/competencies, and demonstrating inter-/cross-disciplinary skills/literacies)
Kipper et al. (2021)	Skills and knowledge	By using a bibliometric approach, the authors develop a science mapping about different aspects of the Industry 4.0. Results indicate that leadership, strategic view of knowledge, self-organization, give and receive feedback, proactivity, creativity, problem solving, interdisciplinarity, teamwork, collaborative work, initiative, communication, innovation, adaptability, flexibility, and self- management are considered as crucial skills for the industry 4.0. Further, authors suggest that knowledge in information and communication technology, algorithms, software development and security, automation, sustainable development techniques, data analysis, and general systems theory.
Maisiri et al. (2020)	Skills	The authors propose a two-skills framework grouped into technical skills (i.e., technological, programming, digital) and non-technical skills/soft skills (i.e., thinking, social, personal). A comprehensive list of 39 skills descriptors are presented in the different skills sub-categories that compose both skill categories.
Prifti et al., (2017)	Competencies	The authors adapted the Great Eight Competencies Model (Bartram, 2005), by relating three variants of competencies, that is, information system, computer science and engineering competencies. A comprehensive list of 68 competencies are considered as relevant personal resources for the industry 4.0.
Silva et al. (2019)	Competencies	The authors present the specific competencies related to the main ten professions in the industry 4.0. For example, a project manager would need the following competencies: environmental responsibility, perspectives and future vision, ability to track changes globally, entrepreneurial thought, creativity, innovation, communication at a global level, leadership, ease of conflict resolution, quick responses to organizational problems, critical thinking, analytical skill, and knowledge.
van Laar et al. (2020)	Skills	The authors propose a 21st century digital skills framework composed by core skills (i.e., technical, information management, communication, collaboration, creativity, critical thinking, problem solving) and contextual skills (i.e., ethical awareness, cultural awareness, flexibility, self-direction, lifelong learning).

Note. These reviews are based on different research databases, scope and search period.

1.3. Method

1.3.1. Scoping Review

To screen the size and scope of the existing records, as well as to refine the search terms and criteria for including/excluding literature, we conducted an initial search of existing systematic literature reviews on Industry 4.0 before the current work. At the best of our knowledge, and after this initial search screening in different broad databases (e.g., Google Scholar, Web of Science), we identified few reviews specifically focused on skills in the industry 4.0 with valuable inputs not only to evaluate the state of the art but also different approaches related to this area (Chaka, 2020; Kipper et al., 2021; Maisiri et al. 2020; Prifti et al., 2017; Silva et al., 2019; van Laar et al., 2020). Additionally, we identified a selected sample of 39 peer-reviewed and non-peer-reviewed publications (e.g., reports, case studies, commentaries) provided by the Future Skills Centre (n.d.). All of them allowed us to identify the existing gap that it was addressed in the current literature review through an organizational focus (i.e., organizational research databases), a wide-ranging view (i.e., 10-year review), and an integrative analysis (i.e., developing a framework integrating previous reviews and complementary analysis).

1.3.2. Search Strategy

To identify the current skill frameworks explicitly related to the industry 4.0, a systematic literature review was carried out by following Daniels' (2019) recommendations. First, considered as valuable sources of information for Organizational Psychology and Organizational Behavior (OP/OB) research, the following electronic databases were used to identify the existing literature in English: Web of Science, APA PsycINFO, APA PsycArticles, Business Source Premier, Psychology and Behavioral Sciences Collection, SocINDEX with Full Text, and Scopus. Second, based on prior systematic reviews related to the topic (e.g., Liao et al, 2017; Xu et al., 2018), we used the following keywords: "industry 4.0", "fourth industrial

revolution", and "4th industrial revolution". Likewise, taking into account that other skill-related constructs are used as interchangeable terms in OP/OB research, we selected the following keywords: "skill", "competency", "ability", "capacity". Third, the literature search was restricted to the publication type (i.e. peer-reviewed "articles") and the year of publication (i.e. from 2011 to 2020). The latter is due to the term industry 4.0 was coined in 2011. Fourth, by following the aid of experienced search specialists, the adopted search strategy (based on Boolean operators) was as follows: (("industry 4.0" OR "fourth industrial revolution" OR "4th industrial revolution") AND (skill* OR competenc* OR abilit* OR capacit*)). As a result, 1630 records were founded in all databases (780 records in Scopus, 596 records in Web of Science, and 254 records in the other databases). Finally, additional searches were conducted to identify relevant papers on skills research by contacting OP/OB experts and hand searches. All searches were conducted in January 2021.

1.3.3. Selection of Studies

In order to be included in the current literature review, the record had to fulfill the following criteria: The record must (1) explicitly refers to skills and industry 4.0 (or any other related keyword above presented), (2) explicitly defines - one or more - skills, (3) focus on employees or university students sample in the case of an empirical article, (4) be written in English language, and (5) comes from peer-reviewed article as a source type (books, book chapters, magazines and trade publications were excluded from the search). The records identified in the databases searches were exported to Mendeley software (version 1.19.4) in order to remove the duplicates, resulting in 1118 records. Later, the screening of the records was carried out to determine the eligibility based on the title and the abstract, and the through examining the full article. Each stage and the results of the entire review process is presented in the PRISMA flow diagram (Figure 1.1).

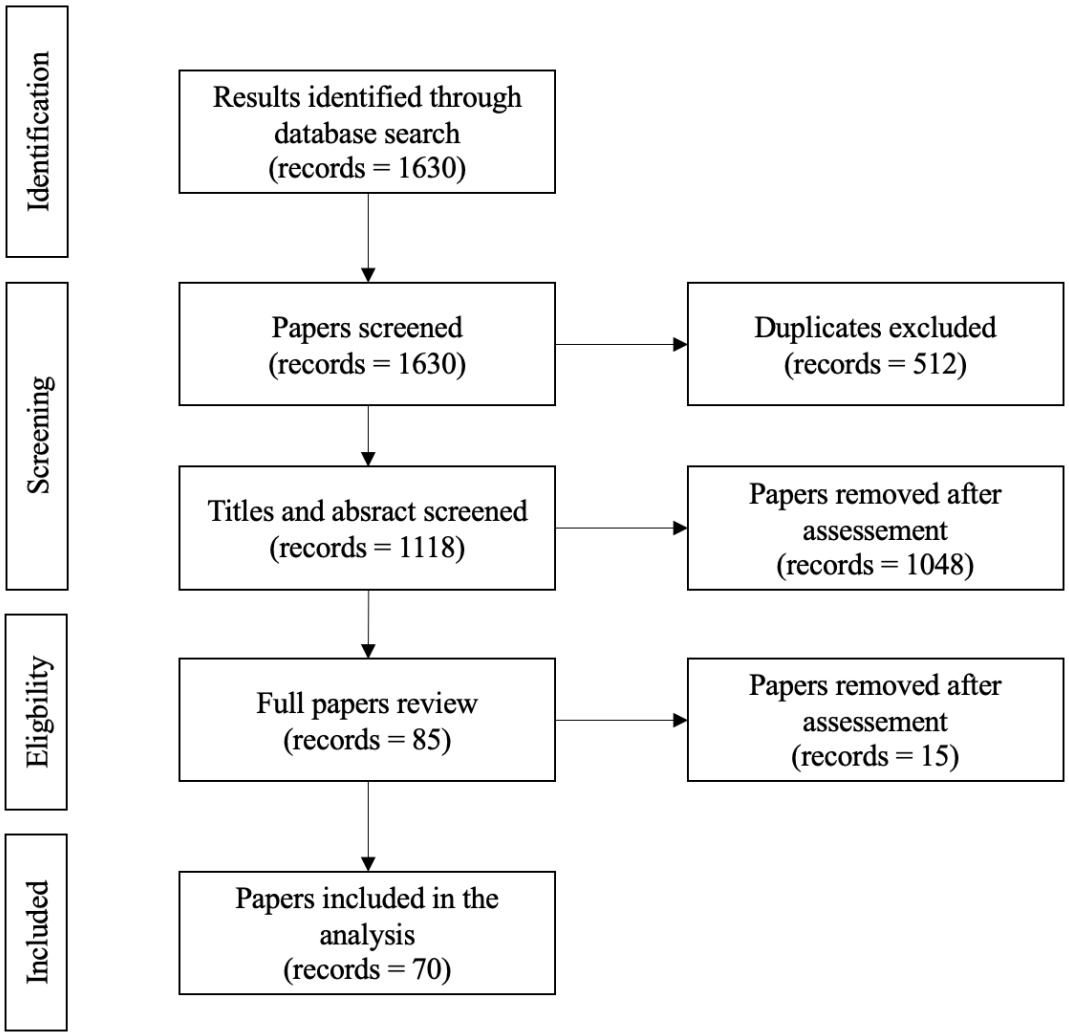


Figure 1.1. *PRISMA Flow Diagram*

1.3.4. Search Results

After a screening of the records, 85 papers were retained to a full-paper review and then, after assessment, 70 papers were considered in the current study. The final database was composed by different descriptors such as authors, studied skills, type of study (e.g., theoretical, empirical), and when applicable research design (e.g., experimental, correlational), used skills measures, sample (e.g., university students, employees), other variables considered in the studies (e.g. antecedents, outcomes), and main results. Thus, from an organizational perspective, the different analysis and classifications were carried out based on such information.

1.4. Results

1.4.1. Descriptive Analysis

Within the 70 papers included in the current analysis, 24% were theoretical (*n* = 17) and 76% were empirical studies (*n* = 53). Regarding the empirical studies, 45% were quantitative (*n* = 24), 40% were qualitative (*n* = 21), and 15% were papers including quantitative and qualitative studies (*n* = 8). Table 1.3 presents information about the study characteristics of the papers included in the current review.

Table 1.3. *Study Characteristics Retained in the Review (n = 70)*

Characteristic	Type	*n*	*%*
Study type	Case-study	16	23%
	Experiment	1	1%
	Cross-sectional Survey	25	36%
	Longitudinal Survey	1	1%
	Mixed-method	8	11%
	Review	2	3%
	Theoretical	17	24%
Sample	University students	18	34%
	Employees	23	43%
	International database	5	9%
	Job descriptors	2	4%
	Firm	2	4%
	Mixed sample	3	6%

Note. These papers integrate sometimes cross-cultural samples.

1.4.2. Content Analysis

1.4.2.1. The most cited skills related to the industry 4.0

Table 1.4 presents the number of skills identified in the seventy selected papers retained in the study and Figure 1.2 shows the distribution of such skills. Fifty-two skills were presented 419 times in the different papers where the most cited I4.0-related skills representing the 59%

(n = 214) of the cases are the following: problem-solving, communication, management, collaboration, creativity, critical thinking, innovation, technical, information and communication technologies, teamwork, technology application, flexibility and leadership. It should be noted that 18 skills (e.g., civic, insight, interdisciplinary, learn from mistakes, task strategies) were used twice and 47 skills (e.g., sales, motivate others, spiritual intelligence) once, having a lower level than three times in the different studies. Consequently, they were not included. Appendix 1 and 2 provide information about the authors, years and the different skill dimensions of the papers used in the current analysis.

Table 1.4. *Number of Times Skills Were Cited in the Studied Papers*

Skill	*n*	*%*
Problem solving	24	6%
Communication	22	5%
Management	21	5%
Collaboration	19	5%
Creativity	19	5%
Critical thinking	19	5%
Innovation	17	4%
Technical	15	4%
Information and Communication Technologies	14	3%
Teamwork	12	3%
Technology application	12	3%
Flexibility	10	2%
Leadership	10	2%
Adaptability	9	2%
Analytical thinking	9	2%
Decision Making	9	2%
Planning	9	2%
Social interaction	9	2%
System thinking	9	2%
Digital literacy	8	2%
Emotional intelligence	8	2%
Self-learning	8	2%
Cognitive	7	2%
Ethical	7	2%
Language	7	2%
Entrepreneurial thinking	6	1%
Lifelong learning	6	1%

Skill	*n*	*%*
Multicultural	6	1%
Programming	6	1%
Service orientation	6	1%
Self-awareness	5	1%
Technology development	5	1%
Conflict solving	4	1%
Empathy	4	1%
Professional development	4	1%
Self-regulation	4	1%
Social influence	4	1%
Visionary	4	1%
Agility	3	1%
Business	3	1%
Digital security	3	1%
Information literacy	3	1%
Marketability	3	1%
Methodological	3	1%
Negotiation	3	1%
Professional	3	1%
Research	3	1%
Resilience	3	1%
Social awareness	3	1%
Soft	3	1%
Teaching	3	1%
Technology design	3	1%

Note. Skills presented only twice were not reported in the current table.

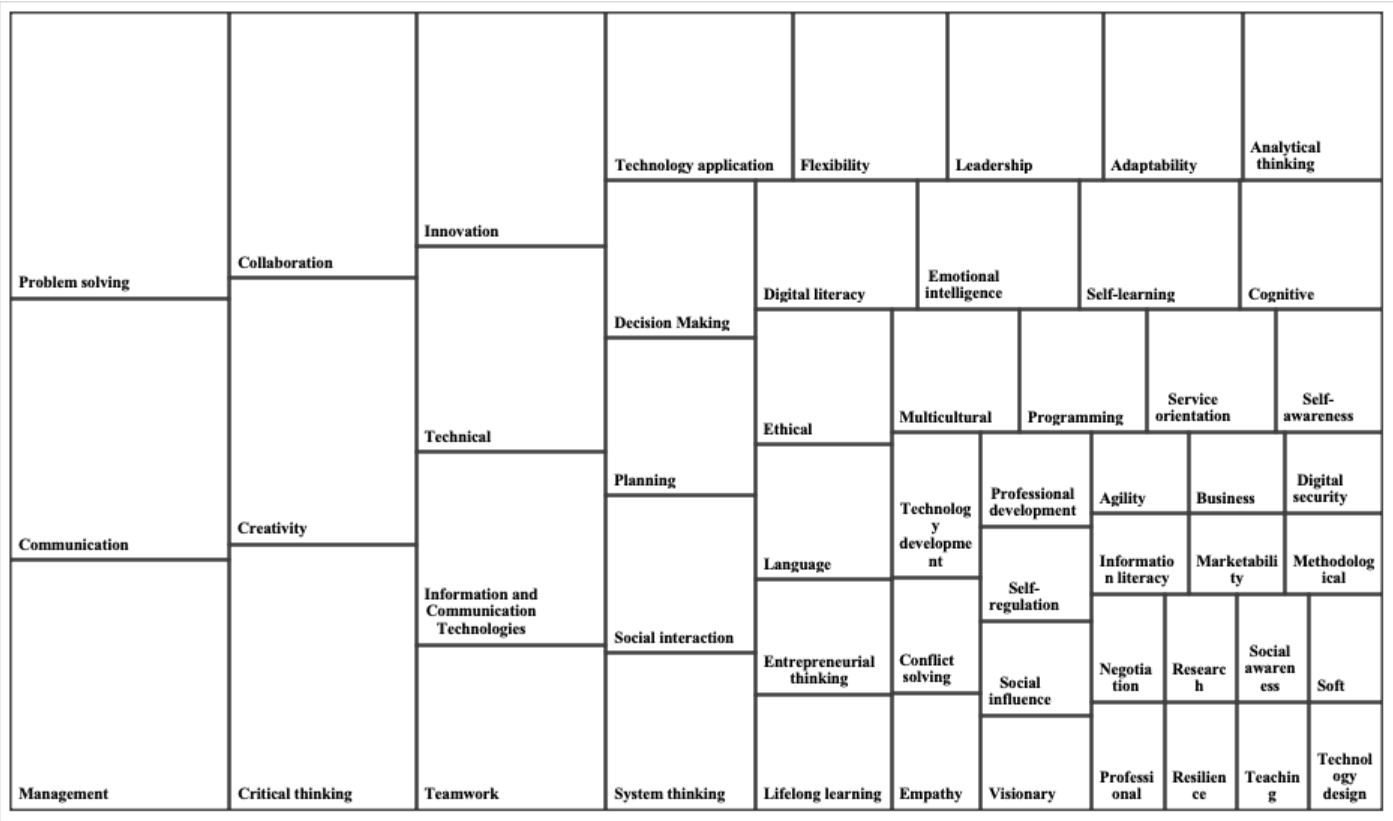


Figure 1.2. *Distribution of Skills Related to the Industry 4.0*

1.4.2.2. Skills Related to Specific Sectors

Over the last ten years, some research has been carried out to explore the skills necessary to deal with the organizational requirements of specific higher education and work-related sectors and roles such as automotive, higher education, engineering, and management. For instance, Le et al., (2020) state that the most relevant skills to prepare undergraduate students for the challenges of the I4.0 are lifelong learning, creativity and innovation, expertise and digitalization, adaptability, critical thinking and problem solving, foreign language, organizing and managing ability. In case of the automotive industry, Jerman et al., (2020) considered that skills as flexibility/adaptation to change, technical literacy, information and communication technologies literacy, innovation and creativity, soft skills and openness to learning are key to face the challenges of smart factories. Regarding the human resource management, Piwowar-Sulej (2020) suggests four-related cluster of skills, that is social (e.g., communication and cooperation), methodological (e.g., analytical competence), personal (e.g., willingness to learn) and domain (e.g., digital networks).

1.5. Discussion

1.5.1. Relevant Skills in the Industry 4.0

The first goal of the current review was to identify the skills related to the I4.0 over the last ten years. Based on the findings (70 papers), we identified fifty-two skills where the top ten relevant skills (in terms of the number of times they were treated in the articles) in the digital age are the following: problem solving, communication, management, collaboration, creativity, critical thinking, innovation, technical, and information and communication technologies (ICT). Nevertheless, it should be pointed out that these skills are only a referential number of skills as many others personal (e.g., knowledge, abilities) resources that are also required in the I4.0, as can be seen in table 4.

1.5.2. Relationship with Other Industry 4.0-related Skill Frameworks

The current findings are consistent with existing skill frameworks related to the technological evolution of the world of work (e.g., Chaka, 2020; Kipper et al., 2021; van Laar et al., 2020). For example, van Laar et al. (2020) proposed the 21st century digital skills framework, a model whose skills can be grouped into two clusters: core skills (i.e., essential skills to deal with tasks and duties required in different occupations) and contextual skills (i.e., skill enabling us to take advantage of core skills). Two major contributions of the Van Laar et al.'s (2020) proposal are reflected through their effort to integrate 21st century societal challenges and the ongoing digital evolution and the development of a broad theoretical skill framework in the advent of the I4.0. A conceptual revision shows that the skills presented in the 21st century digital skills taxonomy (e.g., critical thinking, problem solving, collaboration) were the same to those found in the current review, except for self-direction which, however, is also related to other skills (e.g., self-regulation, self-learning). It has been noted that even though the skills were clearly presented/defined (focused on ICT), the difference between the two skill clusters seems less evident. The latter shows the need for further analysis and discussion about the functional capacities of the skill clusters whose parts act as an "interconnected network" rather than a sum "single entity".

Grounded on the Great Eight Competencies model (Bartram, 2005), Chaka (2020) proposed an adapted version of such model which incorporated the following three new clusters of competencies: job-related skills/competencies (i.e., skills linked to specific industries, roles, activities and technologies such as marketing and industry 4.0 skills), language-specific skills/competencies (i.e., skills enabling effective communication such as reading, speaking, listening, and writing), and inter/multi/cross-disciplinary skills (i.e. transversal skills supporting the work in different contexts such as digital and foundational skills). The Chaka's (2020) framework sheds light on how individuals need to develop some competencies to face the I4.0

challenges by articulating some generic skills (e.g., problem solving, communication, creativity) into the eleven clusters of competencies but also presenting skills specifically related to I4.0 technologies (e.g., data analytics, programming, data-driven decisions). In the same vein, another proposal focused on engineering fields (Prifti et al., 2017) adapted the Great Eight Competencies by articulating these competences into the following three clusters: information system, computer science and engineering competencies. Overall, despite the large number of skills grouped into the Big Eleven competencies framework (Chaka, 2020), it can be seen that these skills do not differ from those identified in this review review. Notwithstanding, the Chaka's (2020) work, as many other reviews, that there is a need for the development of a better conceptual delimitation not only of skills but the different skill clusters.

More recently, based on a bibliometric approach, Kipper et al. (2021) provide an overview of I4.0 competence which includes skills (e.g., creativity, problem solving, teamwork, communication) and knowledge (e.g., general systems theory, sustainable development theory, software development and security). Furthermore, such skills and knowledge are also related to specific advanced technologies (e.g., artificial intelligence, collaborative software, additive manufacturing, robots). In fact, Kipper et al. (2021) argue that skill development should be designed taking into account a new work environment, named as "learning factories", which creates new opportunities and experiences to develop a skillful workforce. As in the previous frameworks, the skills identified in our review are similar/related to those presented in the conceptual map of the competencies required by I4.0 (Kipper et al., 2021).

Considering the above, four elements of analysis come out of the review of these existing frameworks (e.g., Chaka, 2020; Kipper et al., 2021; van Laar et al., 2020). First, the skills identified in our 10-year systematic review on I4.0-related skills (see Table 1.4) are similar to those evoked in previous reviews. Second, in most cases, skills are grouped into broad general clusters (e.g., soft and hard, technical and non-technical, core and context), making it

difficult to understand the functional value of these skill clusters (as an interconnected network). Third, besides the complexity to clearly define some skills sharing conceptual similarities (e.g., creativity and innovation, digital literacy and information literacy), it becomes necessary further analysis of the conceptual delimitation (e.g., characteristics, implications) of skill clusters. Fourth, considering organizational context (e.g., technologies, social support, leadership) becomes more relevant to better understand the value of different skills and how these are permanently shaped by organizations in I4.0.

1.5.3. Building the Workforce of Tomorrow: A Human-Agency Skill Framework

Coherently with our second goal, and considering fast, radical and complex changes of the world of work, it is necessary to develop a skill framework which articulates skills into a functional set of capacities fostering human capacity to adapt to the I4.0. To ensure a successful and sustainable transition to the new world of work where digital, interconnected and smart technologies are becoming the rule rather than the exception, it is required not only an appropriate technological infrastructure but equally a skillful workforce (Ackerman & Kanfer, 2020; Odoardi, Battistelli & Peña-Jimenez, 2021). Nevertheless, while significant efforts have been made to identify I4.0 skills, few of them provide a taxonomy identifying the functional value of skill clusters (van Laar et al., 2020).

We consider that exploring skill clusters or functional capacities rather than particular skills can provide a more realistic view of the individual capacity to perform well her/his work-related activities for three reasons. First, there is no consensus about the conceptual delimitation of some skill-related constructs (e.g., creativity and innovation, self-direction and self-management, flexibility and adaptability) which makes difficult appropriately analyze and assess such skills. Second, the evaluation of the organizational correlates and/or outcomes of specific skills may be particularly difficult, if not impossible, considering that real organizational challenges demand a complex and interrelated set of personal resources (i.e.,

knowledge, abilities, attitudes), including different skills. Third, within an organization, the skill development strategy is built upon different initiatives and learning experiences (e.g., training programs, HR practices, policies), which implies that evaluating how these strategies can impact the development of capacities becomes more plausible than specific skills.

Based on an agentic approach (Bandura, 2006, 2018), the above-mentioned conceptualization of I4.0, and the results from this systematic review, we propose the "Human-Agency Skill Framework" focuses on the development of the capacity of individuals to control their environment through five related and functional skill clusters. According to Bandura (2001, 2018), human agency refers to the human capacity to exert control over our environment, playing a key role in our adaptation, self-development and self-renewal over time. Consequently, developing the individuals' capacity to deal with a more and more complex and fast-changing work environment opens up the possibility to focus on organizational-related capacities rather than possessing skills. In addition, three core properties distinguish the human agency: (1) *forethought* (i.e., developing a representation of desired/expected future as guides and motivators of individual action), (2) *self-reflectiveness* (i.e., reflecting on the meaning of pursuits, personal efficacy and the implications of individual actions and thoughts), and (3) *self-reactiveness* (i.e., developing self-regulation efforts to execute actions plans oriented to attain goals).

Previous conceptualizations and research on skills show that the functional capacity of different skills can be understood through the following clusters: cognitive skills, interpersonal/managing people skills, functional business skills and strategic skills (e.g. Mumford et al., 2007; Peña-Jimenez et al., 2021). Further, due to the current technological leap, technological skills are increasingly relevant for the workforce (e.g., Chaka 2020; van Laar et al., 2020). Thus, we integrate the skills found in the current review along with other skills coming from other frameworks in the skill clusters presented below.

1.5.3.1. The Cognitive Side: Cognitive Skills

The cognitive skill cluster refers to the foundational cognitive capacity to collect, analyze, and use personal knowledge and different types of available information to combine them into a source to better understand and solve problems. Some examples of cognitive skills coming from our review are as follows*: problem solving* (i.e., using knowledge and information to understand and solve a problem), *creativity* (i.e., generating novel ideas allowing creating different ways to solve a problem situation), *analytical thinking* (i.e., analyzing problems through the identification of their key components/patterns), *critical thinking* (i.e., using evidence and reasoning to make choices and judgments of a given situation/problem), *information literacy* (i.e., selecting and using the most valuable and appropriate source of information). Other examples of basic cognitive skills coming from research on skill requirements are *active learning* (i.e., searching opportunities to learn and understanding how new information may help to solve problems), reading comprehension (i.e., processing and understanding written information) and oral expression (i.e., transmitting information and ideas in a clear and effective way) (Mumford et al., 2007; Peña-Jimenez et al., 2021).

1.5.3.2. The Social-Emotional Side: Interpersonal and Managing People Skills

People are embedded within a social system, interacting with one another through face-to-face (e.g., physical workplace) or virtual (e.g., videoconferencing technologies) settings. Interpersonal and managing people skills concern the capacity to interact and work with others as well as negotiate, and influence others to appropriately face the organizational demands. As a result of our review, the skills comprising this cluster are *collaboration* (i.e., sharing information, expertise, resources and/or the workload with others to achieve team goals), *social interaction* (i.e., interacting with others – individuals, teamwork, business units – and regulating of his/her ow actions within a given social context), *conflict solving* (i.e., understanding the source of conflict and/or stressful situations to explore and solve the best solution possible

within a social environment), *multicultural* (i.e., respecting cultural diversity through the understanding and awareness of different cultural backgrounds), *emotional intelligence* (i.e., understanding and managing our own emotions as well as empathize with others' emotions). Along the same lines, others (Mumford et al., 2007; Peña-Jimenez et al., 2021) propose some skills such as *people management* (i.e., managing, developing and motivating others – colleagues, subordinates - while they work, identifying how each one can contribute to meeting the team goal), *social perceptions* (i.e., understanding others' states and emotions and how they act because of that), *persuasion* (i.e., persuading others to adopt goals, plans and or behaviors needed to attain the work-related goals), and *training and teaching* (i.e., developing others' skills through formal and informal leaning experiences at work).

1.5.3.3. The Structural Side: Functional Business Skills

Individuals perform their activities in a given environment having specific explicit and implicit ways of doing things. Functional business skills refer to the capacity to identify and understand how a given system (i.e., market, organization, business unit, team) operates to develop ways of improving work-related processes. Skills comprising this cluster are *business* (i.e., understanding the value chain, processes and core activities of an organization), *service orientation* (i.e., seeking ways to help clients and/or colleagues and ensuring the quality standards) and *entrepreneurial* (e.g., identifying how a specific market operates in order to find potential niche business opportunities). Other specific skills from skill-related frameworks are *resource management* (i.e., determining the most effective and efficient way to use organizational-related resources to perform work-related tasks), *operations analysis* (i.e., identifying ways to optimize business operations through the historical pattern of organizational performance), and *report formulation* (i.e., creating and transmitting business reports with valuable information to make well-informed decisions), (Mumford et al., 2007; Peña-Jimenez et al., 2021).

1.5.3.4. The Technical Side: Technological Skills

In the digital age, organizations are integrating technologies (e.g., drones, cloud computing, 3D printing) that are transforming not only the business products and services but also the way we work and interact with other people within and outside the organization. The cluster of technological skills refers to the capacity to identify, use and integrate the potential value of technological development to better perform work-related duties. Based on our finding, examples of skills comprising this skill cluster are *technical* (i.e., recognizing the main characteristics and functionalities of technical devices, software, tools and how these can be used to perform and enhance our activities and duties), *information and communication technologies* (i.e., handling ICT necessary and available to our work-related activities), *technology application* (i.e., identifying how core aspects of technologies may be used to improve human-machine synergy), *programming* (i.e., understanding and using programing language to create, modify and enhance computer and/or digital software), and *digital security* (i.e., identifying existing and potential vulnerabilities due to integration of digital technologies). Although technological skills may be related to the specific technological structure embedded within the organization, the type, complexity and evolution of this skill cluster also depend upon the occupation, organizational role, tasks and duties of the staff involved.

1.5.3.5. The Strategic Side: Strategic Skills

Nowadays, individuals need to rapidly adapt, made decisions and act to attain goals within a more and more uncertain, virtual, complex and interconnected world of work (Battistelli & Odoardi, 2018). Strategic skill cluster refers to the capacity enabling the strategy development as well as the decisional processes at work (from goal setting to work-related action). From our review, some examples of these skills are the following: *visioning* (i.e., visualize or anticipate how an organization/business unit/team/ process can be improved or work under ideal conditions), *planning* (i.e., creating and adapting action plans to meet work-

related goals), *decision-making* (i.e., exploring and evaluating environment to make decisions allowing to adopt the best possible goal/solution/action plan in a given problem situation), and *self-regulation* (i.e., monitoring and managing our environment and behavior to determine the energy and efforts necessary to attain a work-related goal). Other skills related to this cluster are *problem identification* (i.e., detecting and understanding existing and potential problems that we may have in a given work context), *solution evaluation* (i.e., determining the implications of a course of action and how alternative solution may contribute to solving work-related problem) and *identification of causes and consequences* (i.e., scanning work environment to identify causal relationships and potential outcomes impacting work goal attainment) (Mumford et al., 2007; Peña-Jimenez et al., 2021).

Summarizing, the human-agency skill framework is composed of cognitive, interpersonal/managing people, functional business, technological, and strategic skills which are considered as different but interrelated capacities. Furthermore, in consistence with an agentic approach (Bandura, 2001, 2018), the current framework distinguishes three different roles among the skill clusters: 1) strategic skills have a "*core*" role since they provide individuals the capacity to develop their forethought, self-reactiveness, and self-reflectiveness; 2) cognitive skills and interpersonal/managing people skills have an "*enabling*" role because these are related foundational cognitive, social and emotional processes; and 3) functional business skills and technological skills have a "*enhancing"* role because these allow not only a better view of the organizational dynamic but also these are supported to assisting, arresting, augmenting and/or automating technologies. Figure 1.3 depicts the different axis of the human agency skill framework.

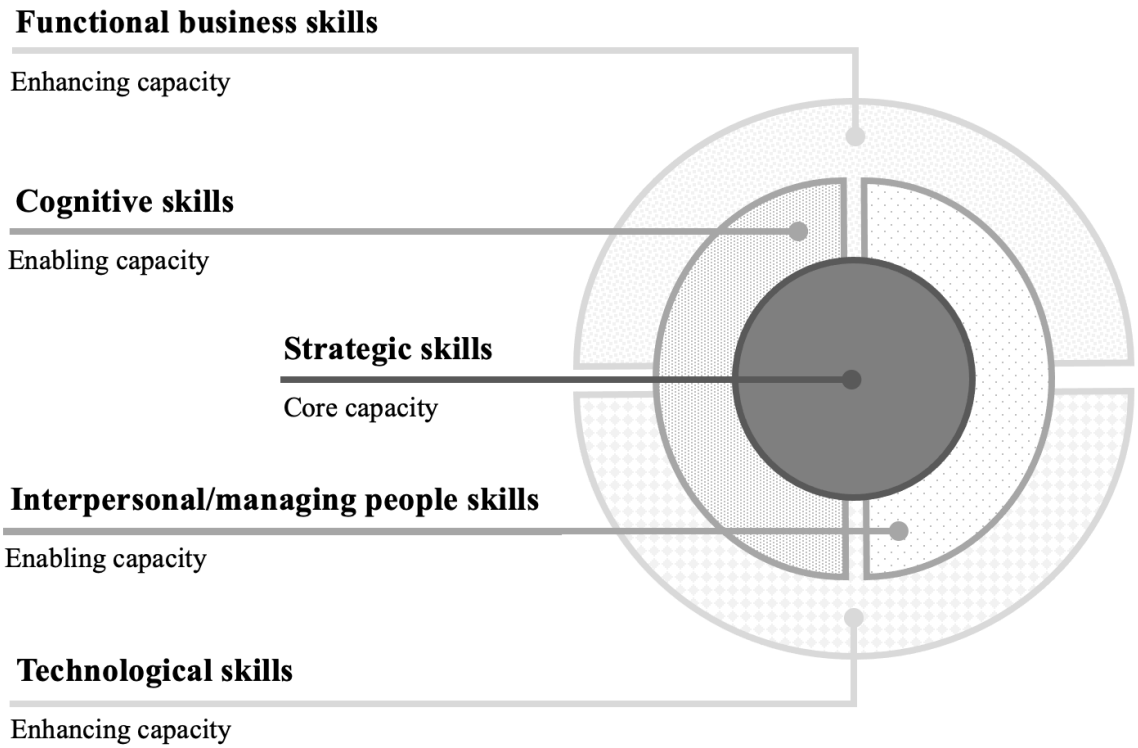


Figure 1.3. *The Human Agency Skill Framework*

1.5.4. Limitations

Although the current review provides a state of the art of different skills related to the I4.0 as well as a source to develop a human-centered skill framework, there are some limitations that must be considered. First, from a theoretical perspective, even though I4.0 is a term widely used by OP/OB scholars and practitioners, there is many other umbrella concepts (e.g., 21st century, digital) or specific technology-related terms (e.g., internet of things, smart factory) referring the societal and technological change of the world of work as can be seen in other reviews/frameworks (e.g., Chaka, 2020; Kipper et al., 2020; van Laar et al., 2020). Skill is another concept having similarities with other human capital-related constructs (e.g., ability, capacity, competency) and despite including them in our review, there are many other sometimes used as interchangeable terms (e.g., intelligence, orientation) which were not

incorporated in our review. From a methodological standpoint, we focused our review in a time frame that allowed us to do a 10-year balance (from 2011 to 2020) of the most relevant skills related to the I4.0, yet the search strategy excluded other potential insightful skills. In addition, our findings used peer-reviewed papers (in English) as a key element of analysis, thus excluding consultancy, national and/or international reports. Last, from a practical view, the current analysis considered the most relevant skills in the I4.0 (in terms of the number of times they were presented in the papers), thus precluding specific emerging skills.

1.5.5. Future Research Agenda

The current work allowed us to identify different research avenues. Regarding the literature review, further research is needed to identify the most relevant personal and contextual correlates (e.g., antecedents, outcomes) of skills as well as mediating and moderating processes. Furthermore, as it has also been noted by other reviews (e.g., Chaka, van Laar et al., 2020), most research has evaluated skills by using descriptors and self-reported measures which provides indirect measures of the self-perceived capacity, but at the same time the need for developing complementary forms of skill assessment (e.g., performance indicators, situational judgment tests). With regard to the human agency skill framework, further theoretical development and research is needed to better understand, analyze and evaluate: 1) how skills become or act in the form of an integrated capacity (in lieu of several pieces of a mosaic), 2) how these different capacities change over time (rather than stable capacities), 3) how these skill clusters are developed/constrained by the organizational context (instead of available personal resources) and 4) the way we transform these individual capacities into collective capacities (e.g., teams, business units, organization). Moreover, although all the skill clusters play an important role to develop the individuals' agency, a strategic skill deserves special attention considering its core function to develop human agency.

1.5.6. Conclusion

The world of work is undergoing major changes because of technological evolution and as a result, there is an urgent need for developing individual's capacity to perform their work-related within a fast-changing, virtual, complex and interconnected organizational environment, also known as industry 4.0, which is supported by assisting, arresting, augmenting and/or automating technologies. The current work allowed us to identify 52 significant skills (e.g., problem solving, communication, management, collaboration, creativity, critical thinking, innovation, technical, and information and communication technologies) linked to the industry 4.0. Based upon our theoretical background and findings, we developed the human agency skill framework whose focus is to develop the human capacity to exercise control over work-related environment, and which is composed of core (i.e., strategic skills), enabling (i.e., cognitive skills, interpersonal/managing people skills) and enhancing (i.e., functional business skills, technological skills) capacities. In this way, we hope to contribute to identify not only the skills required in the industry 4.0 but also to better understand how such skills become a functional and valuable capacity not only for organizations but also for employees.

1.6. References

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Chapter 2

Exploring Skill Requirements for the Industry 4.0

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Chapter 2. Exploring Skill Requirements for the Industry 4.0

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

2.1. 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.

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 sheds 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.

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.

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

*2.2.1. 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).

2.3. Study 1: Perceived Skill Requirements in the Industry 4.0

2.3.1. 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).

2.3.2. Method

2.3.2.1. 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.

2.3.2.2. 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.

2.3.2.3. 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*).

2.3.2.4. 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.

2.3.2.5. 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.

2.3.3. 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 2.1 presents the factor loadings of the 4-factor model, and Table 2.2 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.

2.3.3.1. 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).

2.3.3.2. 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).

2.3.3.3. 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).

2.3.3.4. 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).

Table 2.1. *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 2.2. *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; ** = $p < .01$.

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 2.3.

Table 2.3. *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; *** = $p < .001$.

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

2.4.1. 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.

2.4.2. Method

2.4.2.1. 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).

2.4.2.2. 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.

2.4.2.3. 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).

2.4.2.4. 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.

2.4.2.5. 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.

2.4.3. 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 2.4 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 2.5.

Table 2.4. *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 2.5. *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 2.6.

Table 2.6. *Main Results of the Latent Growth Curve Analysis Comparison Between Time 1 and Time 2*

Model \ Main DV	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). * = $p < .05$; ** = $p < .01$.

2.5. 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).

2.5.1. 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.

2.5.2. 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.

2.5.3. 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.

2.5.4. 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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Chapter 3

Conceptual and Measurement Development of the Strategic Skills Questionnaire

This chapter is in preparation to be submitted for publication:

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Chapter 3. Conceptual and Measurement Development of the Strategic Skills Questionnaire

Abstract

A growing digital and changing world of work, also known as industry 4.0, has shown the importance of developing the workforce to seize the opportunities of this increasingly technological-driven world. However, while a considerable effort has been made to identify technical and/or occupational skills, the skills allowing individuals to adapt themselves and transform their environment have received less attention. Based on the agentic social cognitive theory, this work presents the conceptual development and validation of the strategic skills questionnaire which measures the anticipating, scanning, connecting, goal setting, planning, monitoring and enacting skills supporting the strategy-making process at work (from situational appraisal to strategy implementation). Through two cross-sectional studies, an exploratory (n = 253) and confirmatory (n = 292) factor analysis revealed a seven-factor structure. Likewise, the strategic skills were positively related with general self-efficacy and learning goal orientation, while no statistically significant relationship was found among these skills and performance and avoidance goal orientation (except for three skills). The findings provide evidence of the adequate psychometric properties (i.e., validity, reliability) of the strategic skills questionnaire, and consequently, the theoretical and practical implications of these skills are discussed.

Keywords: strategic skills, human agency, digital age, measurement, validation

3.1. Introduction

In the midst of an era where smart, digital and interconnected technologies (e.g., artificial intelligence, cloud computing, drones) are engendering several, complex and rapid changes worldwide, it is becoming increasingly evident that society needs to develop skillful people to overcome the challenges of a new world of work and organizations in the 21st century, also known as "Industry 4.0" or "Fourth Industrial Revolution" (Ackerman & Kanfer, 2020; Battistelli & Odoardi, 2018). Individuals, teams and organizations need to be prepared not only for adapting to a more changing and challenging work environment, but also and even more importantly, to transform it in a proactive, engaged and structured way (Parker & Bindl, 2017; Peña-Jimenez et al., 2021). It is therefore necessary to examine and evaluate skills that become essential to allow people to set goals, made decisions, planning their actions and proactively act to attain their goals, thus allowing them to adapt themselves as well as transform their surrounding environment.

Skills are considered as a set of capacities enabling individuals to successfully perform a task in a given context, which are developed by different learning experiences (e.g., formal training, informal work activities) (McClelland, 1973; Roe, 2002), and are considered as good predictors of job proficiency (Carpini et al., 2017). Skills represent a major asset that must be developed (e.g., upskilling, reskilling), especially in times where smart technologies are changing the way we work and how we interact with others inside and outside the organizational system (Ackerman & Kanfer, 2020; Kanfer & Blivin, 2019). Most current research has provided us skill frameworks related to specific technologies (e.g., van Laar et al., 2018) and/or occupations (e.g., Dierdorff & Elligton, 2019). For instance, Neubert et al., (2015) consider that complex and collaborative problem solving are two essential skills spanning multiple work domains. Likewise, Van Laar et al., (2018) proposed the 21st century digital skill framework (having a special focus on information and communication technologies) which is

composed of creativity, critical thinking, collaboration, communication, information management, problem solving and technical skills.

Traditional approaches in skill research (e.g., Dierdorff & Elligton, 2019; Van Laar et al., 2018) provide an interesting view on how world (e.g., social and labor trends, specific technologies) dictates and shape the human behavior which, in turn, will lead to identify the skills needed to be developed to prepare the workforce to overcome such requirements (e.g., job position, organizational, industrial sector). Instead, the agentic and proactive approaches highlight the importance of developing the individuals' capacity to change their life courses and exert control over their environment, thus offering a complementary but essential view of how humans can handle challenging and changing situations (Bandura, 2018). Thus, according to the second approach, rather than focusing on specific skills (e.g., digital, functional, occupational), exploring and developing essential skills to evaluate and anticipate future changes, make strategic decisions, and design and execute strategic planning in times of uncertainty (e.g., global pandemic) and complexity (e.g., technological advancement) open up new avenues for understanding human development at work (Ackerman & Kanfer, 2020; Parker & Bindl, 2017).

Grounded on non-mechanistic human action approaches (for a review see Kanfer et al., 2017), some have proposed different frameworks and instruments to better understand and assess agentic - strategic capacities or behaviors. For example, by using a managerial model, Parente et al. (2012) developed a measure of a single factor structure of strategic skills acquisition in a sample of university students. Likewise, Bindl et al. (2012) proposed a scale to measure envisioning, planning, enacting, and reflecting behaviors at work, by using a goal-regulation model which is not so different from the postulates of the human agency (Bandura, 2006). Vähäsantanen et al. (2019) developed an instrument to measure the professional agency at work, a multidimensional structure composed of three dimensions (i.e., developing work

practices, influencing at work, negotiating professional identity), which has a subject-centered sociocultural background. More recently, Cenciotti et al. (2020) developed the work agentic capabilities questionnaire to assess a four-factor model of the human agency, in terms of the forethought, self-regulation, self-reflection, and vicarious capabilities, thus providing us with an instrument to assess three core properties of the human agency and a valuable personal resource (Bandura, 2018). In this way, even though some efforts have been made to understand and study strategic capacities supporting the human agency (Bandura, 2006, 2018), there is a need for further theoretical development as well as measures to understand the human agency at work (Grant & Baden-Fuller, 2018; Cenciotti et al., 2020).

The main purpose of this study is therefore to develop and validate a measure to assess the strategic skills, which is composed of different but related capacities supporting the agentic strategy-making process at work. To attain this goal, first, we develop the theoretical basis of the strategic skills, based on an agentic approach (Bandura, 2006, 2018), and the different phases of the strategy-making process (Gollwitzer, 2018; Roe, 1999a). Second, we test the robustness of the factorial structure of the questionnaire and we then examine the nomological network of strategic skills by exploring their relationship with other variables. Overall, the present study makes three important contributions. First, this study introduces a new instrument to assess different skills fostering the strategy-making process (i.e., situational appraisal, strategy implementation) as a way to develop the human agency, thus expanding the understanding of human adaptation, development and renewal at work. Second, empirical evidence of the psychometric properties (i.e., reliability, factorial validity, nomological validity) of the SSQ are provided, which represents the ground for future studies evaluating other metric qualities. Last, this work gives both organizational scholars and practitioners the possibility to use the SSQ in French-speaking working contexts to assess distinctive strategic skills, or related to different phases of the motivation human action. In this way, we seek to

contribute to expanding the understanding of strategic skills as a way to overcome the work and organizational challenges in the era of smart technologies.

3.2. Strategic Skills

"*The human mind is generative, creative, proactive, and reflective, not just reactive*" (Bandura, 2006, p. 167)

The aforementioned idea represents one of the main postulates of the agentic approach (Bandura, 2018; Strauss & Parker, 2014), which considers that a person intentionally tends to achieve a goal by shaping his or her environment and life courses in an active way. This is also a key cornerstone of the theoretical background on those skills allowing employees to make and execute strategic decisions.

From an ontological standpoint, the current proposal finds theoretical support on a non-mechanistic approach of human action (Bandura, 2018; Kanfer et al., 2017). The "human agency" considers the individual as an active agent whose behavior is the result of cognitive, affective, motivational and selection processes which depends upon personal and environmental factors (Bandura, 2006). At work, job-related action is an intentional and engaged response to achieve a work-related goal, where the psychological self-regulatory process plays an essential role to allocate, choice and use individual capacities (Wood & Bandura, 1989). Bandura (2018) states that the core properties of human agency (i.e. forethought, self-reactiveness, self-reflectiveness) can be considered as enablers of our self-adaptation, self-development and self-renewal over time. Accordingly, in an age where the speed, depth and breadth of social changes because of the technological development (Schwab, 2017), the development of human agency at work can be useful to deal with a more dynamic and complex work context. In this regard, the human agency approach is taken as the basis for the development of the strategic skills through which individuals exercise control over their environment (Bandura, 2006).

According to a process-based approach (Kanfer et al., 2017), many psychological theories state that engaged and motivated human action can be understood through two interdependent systems that govern goal selection (e.g., theory of planned behavior: Ajzen, 1991) and goal enactment (e.g., social cognitive theory: Bandura, 1986). Similarly, other process-oriented models have addressed the exploration of such self-regulatory processes, such as the model of action phases (i.e., pre-decisional, pre-actional, actional, post-actional) (Gollwitzer, 2018) and the calendar model of motivated human action (i.e., generating, filtering, scheduling, preserving, enactment) (Roe, 1999a). All in all, these process-oriented theoretical frameworks suggest that there are different but related phases allowing explore how people face and control their environment. Thus, in accordance with our ontology vision, the social cognitive theory (Bandura, 1986) and action-phases frameworks (e.g., Gollwitzer, 2018; Roe, 1999a) are the theoretical basis to determine and define the strategic skills, thus allowing to consider not only different mindsets (i.e., deliberative, implemental) but also the self-regulation process of motivated human action (from goal intention to goal achievement).

From an organizational viewpoint, the current proposal is grounded on its importance to foster the strategy-making process at work. In the organizational setting, for instance, we can distinguish four stages in the strategy-making process: (1) situation appraisal and diagnosis, (2) strategic option generation, (3) strategic choice and (4) strategy implementation that need different but interrelated resources to transform strategic decisions into goal-oriented actions (Grant & Baden-Fuller, 2018). In an era of turbulent times, individuals and, more importantly leaders, must develop their strategic capacity to cope with a volatile (i.e., unstable change), uncertain (i.e., lack of knowledge/information), complex (i.e., interconnected parts interacting as a whole) and ambiguous (i.e., doubts about) world (Bennett & Lemoine, 2014; Rimita et al., 2020). For example, from a managerial angle, Tett et al., (2000) stated that problem awareness, goal setting and decision-making are essential capacities to ensure organizational performance.

In addition, Mumford et al. (2007) suggest that strategic skills (e.g., evaluating, liaison, planning) are key resources to understand complex environments and cope with ambiguity. In the same vein, Goldman and Scott (2016) presented a strategic thinking competency model (including an extensive list of behavioral indicators) which is composed of visioning, environmental awareness, assessment and evaluation, strategy creation, plan development, implementation, and alignment capacities.

Therefore, we consider that the individual – *strategically* – evaluate scenarios, defines goals, makes decisions and acts considering of his/her personal resources, but equally, environmental factors to face organizational requirements. Unlike other skill categorizations (e.g., technical skills, soft skills, meta skills, etc.), we propose the term "*Strategic"* skills for three main reasons. First, to refer us to those capacities related to the core properties of human agency (i.e. forethought, self-reactiveness, self-reflectiveness), which in turn affect the psychological self-regulation process of motivated human action (from goal setting to goal implementation) oriented to achieve a work-related goal. Second, to denote its value to the strategic-making process at work. Even though the term "*strategy*" refers to different analytic perspectives such as a plan, pattern, ploy, position, and perspective (Mintzberg, 1987), in this work, "*strategy*" is mainly underpinned by a "planning" approach, which can be defined as a "*program of action designed to achieve a goal or accomplish a task*" (VandenBos, 2015, p. 1036). Third, to refer us to its social relevance in times of change (e.g., rising technological evolution, uncertain and critical events like covid-19 pandemic), as a set of capacities allowing people to face a more changing and challenging work environment (Kanfer & Blivin, 2019). In this regard, we propose the following definition:

Strategic skills are the individual's multi-component capacities which facilitate strategy-making process (from situational assessment to work-related action), as well as a strategic enabler of other needed capacities to successfully anticipate and deal with current

and future organizational demands. These are essential capacities allowing individuals to develop, modify and transform their personal, social and organizational resources, in an active, thoughtful, engaged, flexible and intentioned way.

The calendar model (Roe, 1999a), a theoretical framework examining the psychological process behind the individual's work-related action can illustrate how these skills come into play. According to Roe (1999a), this dynamic process can be distinguished by the following phases: (1) generating goals, (2) filtering goals, (3) scheduling goals, (4) preserving goals, and (5) goal enactment. First, *generating goals* refers to the elaboration of goals, a creative process in which employee analyzes and transforms an organizational issue into a source to set a goal in accord with their motives. A goal is considered as a mental representation of a desired state achievable by a committed intention to perform needed behavior(s) which in turn will enable to attain the target state. Second, *filtering* represents an evaluation of the importance of the goal(s) for the organization as well as for oneself, where the individual makes an expressed commitment to the goal (e.g., make agreements, public statements). Third, *scheduling* represents the action planning to achieve the pre-established goals. To do that, people may use internal and external resources to schedule required actions and allocating resources. Fourth, *preserving* is the phase where stored goals in long- or short-term memory are recalled to adapt goals (e.g., re-filtering, re-scheduling) considering potential variations in organizational context and personal interests. Lastly, *enactment* refers to a recalling process of the predefined goal to mobilize the needed energy to execute the goal and achieve the desired state. We consider that for each of these "phases" is possible to identify relevant skills supporting the strategy-making process.

Thus, consistent with this theoretical framework (Bandura, 1986, 2018), we present below the strategic skills through an analysis of the strategy-making process and the action

phases framework of the of motivated human action (Grant & Baden-Fuller, 2018; Gollwitzer, 2018; Roe, 1999a).

3.2.1. Anticipating Skill

Human agency posits that individuals are proactive and engaged agents trying to change their environment (Bandura, 2018). To do this, at work, employees need to be able to develop a representation of the future they want to pursuit or will face. Anticipating skill is defined as the individual capacity that allows envisioning future organizational scenarios or possible outcomes (including possible benefits and costs of pursuing them) as well as developing a mental depiction of how events (including objects and actors around them) may occur in the future (Grant & Ashford, 2008). Empirical evidence suggests that foreseeing and imagining possible future goals motivate people to pursue such goals or self-regulate work behaviors (Gollwitzer, 2018; Locke & Latham, 2019).

In the organizational setting, this capacity to forecast work-related scenarios or requirements seems to be particularly useful for organizations due to its contribution to development of valuable proactive work behaviors (Grant & Ashford, 2008; Parker et al., 2010). For example, Parker and Collins (2010) argue that the envisaged future by the individual can develop different proactive behaviors at work oriented to the person-environment fit (e.g., negotiating workload with supervisor), to improve the internal functioning of the organization (e.g., proposing more efficient work methods), and to improve the fit between the organization and its environment (e.g., adopting new organizational strategy or focus). In the same vein, Montani et al. (2015) has shown that anticipation is related to innovative work behavior through the mediating role of planning behaviors. Therefore, anticipating skill is especially relevant to envision future scenarios, thus allowing individuals have valuable information to make decisions, set goals and to develop appropriate action plans to pursuit the desired future.

3.2.2. Scanning Skill

Defining a goal requires an appropriate diagnostic of potential elements that enable or limit the goal achievement. Scanning skill is a relevant capacity which is defined as the search for change events in the environment having a – direct or indirect – impact as well as – current and/or future – implications to the achievement of work-related goals (Mumford et al., 2007). From a strategic standpoint, scanning can be considered as an activator of strategic interpretation and action (Dutton & Duncan, 1987). Scanning is therefore an ongoing evaluation of the individual's environment used to determine, for instance, a potential event that "don't fit" with the expected work environment (Mumford et al. 2007).

Empirical evidence suggests that scanning has a valuable role to the interpretation and action, as well as an indirect effect of some organizational performance outcomes (e.g., Beal, 2000; Thomas et al., 1993). Ford and Gioia's (2000) results suggest that scanning internal and external events are important for the problem-solving process. Likewise, Nag and Neville (2020) founded that scanning also offers social learning opportunities that improve the levels of self-efficacy which in turn influences organizational innovation and performance. Accordingly, scanning can be considered as a supporting deliberating cognitive resource to identify and anticipate problems and opportunities to establish work-related goals but also to redefine actions plans to deal with significative events.

3.2.3. Connecting Skill

In the digital era, workforce is exposed not only to permanent change but also to a more interconnected work environment (Battistelli & Odoardi, 2018). Cognitive researchers argue that there are cognitive structures, known as prototypes, which contain a set list of attributes responsible for the identification, categorization and processing of concepts and objects (Cantor et al., 1982; Schenider & Blankmeyer, 1983). In line with this premise, organizational system can be considered as a network of interconnected nodes and consequently, individuals build a

cognitive representation of what it occurs or how the organizational system works. For instance, an implicit leadership model (Lord et al., 2001) claim that the representation of a leadership prototype is based upon several contextual factors (i.e., culture, leader, follower, task) and four lower order factors (i.e., affect, values, goals, norms). Therefore, the categorization of a leader is the result of the information received but also the way the information is connected (due to the relationship of nodes) by the individual. Similarly, Lowman (2019) proposed a model of how employees' understanding affects the individual's representation of the ideal organization.

Connecting skill refers to the individual capacity to identify and connect objects and/or events within the organizational, connecting them to identify how the organization works (Mumford et al. 2007). For instance, employees generally must acknowledge and make sense a huge amount of labor contingencies (e.g., stakeholders demands, internal and external requirements) not only during the goal-setting phase but equally after the work-related goal was reached. Therefore, we consider that the capacity to connect different factors/events composing the organization represents a strategic skill due to its value to make an appropriate organizational diagnosis (Gollwitzer, 2018; Roe, 1999a).

3.2.4. Goal Setting Skill

After an appropriate situational appraisal and the formulation of possible alternatives to deal with an organizational requirement, making a strategic choice is an important stage in the strategic-making process (Grant & Baden-Fuller, 2018). In this regard, goal setting skill is defined as the reflective process of identifying something that an individual want to accomplish (challenging but feasible) to cope with an organizational requirement and/or issue in a given period of time (Gollwitzer, 2018; Locke & Latham, 2019). From an organizational perspective, we can distinguish between goals defined by others such as supervisors or managers (i.e., goals-as-given), and those goals defined by the own employee (i.e., goals-as-set); nevertheless, in this paper the goal is a well-defined intention and representation of a desired state after a thorough

evaluation and decision-making (Gollwitzer, 2018; Roe, 1999a). In other words, goal is seen as the combination of a cognition, intention and commitment related to possible work-related actions (Roe, 1999a).

Forming a goal intention is considered as an enabler of valuable workplace outcomes (Locke & Latham, 2019). For example, psychological research has shown that employees with specific and challenging work-related goals show higher levels of job performance (e.g., Chen et al., 2021; Locke & Latham, 2019). Likewise, from an action-phases perspective (Gollwitzer, 2018), the goal intention represents the stage after the evaluation of the perceived feasibility and desirability of the chosen alternative and the transition point towards the phase of goal implementation. Therefore, we argue that goal setting is an essential strategic skill, especially for its contribution to the strategic choice and its motivational effects on performance (e.g., productivity, cost improvement).

3.2.5. Planning Skill

According to *scheduling* phase of the calendar model (Roe, 1999a), employees establish and develop action plans to perform a work-related action. Considering this, planning skill can be defined as a personal capacity to develop an action plan, including coordinating tasks and gathering information/resources, to ensure the achievement of a stated goal (Battistelli et al., 2004; Kantrowitz, 2005; Gollwitzer, 2018). As can be noted, planning is a skill that allows the integration of temporal (e.g., time allocation, postponing actions) as well as contextual (e.g., facilities, logistics) factors related to the planning process (Battistelli & Atzori, 2006). This can be seen, for instance, when people (e.g., project managers) make plans for their duties, and for that, they use internal (e.g., mental note, reminders) and external (e.g., day-planners, week-planners) planning tools, considering also the importance and priority of several demands within the organization.

In a complex and dynamic work environment, planning skill can be a highly valuable capacity for performance effectiveness both at an individual level and at a collective level (e.g., Kantrowitz, 2005; O'Neill et al., 2012). For example, Mintzberg (1975) highlighted the importance of how leaders plan tasks and activities, gather and manage resources, spend their time. Similarly, Gollwitzer (2018) states that adding plans to individual's goals may enhance the rate of goal achievement rather than just goal setting because the individual may manage future situations (considered as opportunities or hindrances). Accordingly, we consider that planning is a capacity facilitating, for example, the *scheduling* phase of the self-regulation process, and consequently, one can prepare reasonable action plans to allow the strategic implementation (Roe, 1999a).

3.2.6. Monitoring Skill

In the real work setting, employees must deal with several coexisting tasks and duties to achieve goals. After carefully evaluate scenarios, make decisions, and establish action plans, people also need to evaluate whether the implementation choice is working as expected either to control its progress or to make corrective plans. Monitoring skill refers to the capacity to control the progress of a specific action plan, as a source to implement actions to deal with a problem or situation (Gollwitzer, 2018; Roe, 1999a). Monitoring is particularly useful to evaluate on how, why and when to use specific strategies as well to reallocate resources or redefine goals (Bandura, 1986; Roe, 1999a). For instance, the unexpected resignation of an employee in an organization may significantly affect the progress of a work project and, in such case, the project leader must evaluate the potential impact, make decisions and adopt new strategies (e.g., redistributing tasks, reallocating a team member, requesting a change in the deadline to finish the project). Consequently, we argue that adjusting goals and strategies requires the capacity to monitor goals advancement and the implications of strategic choices and plans.

According to Bandura (1986), monitoring contributes to the awareness of the individual's strengths and limitations, thus allowing to effectively regulate and allocate resources. For instance, entrepreneurial research has revealed that successful entrepreneurs show higher levels of monitoring than less successful entrepreneurs (e.g., Baron, 2007), and monitoring has a relevant role to develop cognitive adaptability (e.g., Haynie et al., 2012). As a result, monitoring may have a relevant role in the *preserving* phase of the calendar model where employees need to decide whether, considering the continuously changing conditions in work environment as time passes, they may need to redefine their plans but also to decide if the goal is achievable (Roe, 1999a).

3.2.7. Enacting Skill

Strategy-making process is not merely strategic planning but also strategic action, in other words, a competent employee must be an effective problem solver and decision maker but above all a strategic agent for organizational change (Grant & Baden-Fuller, 2018). Enactment skill refers to the individual's engaged actions oriented to implement the previous defined action plans to achieve a goal (Gollwitzer, 2018; Roe, 1999a). According to Roe (1999a), the goal execution can be understood through two main acting phases (i.e., action preparation, action execution) that are implemented in an iterative manner, and which serve as an input to adjust our strategic choice and planning if necessary. It implies that goal enactment is also the result of an action regulatory process based on individual aspects (e.g., mental model of the goal) and contextual factors (e.g., feedback) (Gollwitzer, 2018; Wood & Bandura, 1989). Unlike other valuable individual (e.g., innovation) and collective (e.g., collaborative problem solving) work behaviors, goal enactment represents the physical manifestation of an engaged and planned work-related action, carried out as a preliminary step to reach the goal pursued (Grant & Ashford, 2008; Roe, 1999a). Thus, since the goal achievement depends on many other

work-related actions, enactment represents the materialization of the planning and is, therefore, an essential skill.

To sum up, the strategic skills are the following: anticipating, scanning, connecting, goal setting, planning, monitoring, and enacting. These dynamic and interrelated capacities are considered as key skills due to: (1) the role they can play into the individual's self-regulation process (from goal-setting to job-related action) of human agency, (2) their contribution as enablers or drivers of the strategy making process (i.e., situation appraisal, option generation, choice, implementation), and (3) their value for the adaptation to changing and demanding work environments.

Based on an agentic approach of the Social Cognitive Theory (SCT; Bandura, 1986, 2018), and action-phases frameworks (e.g., Gollwitzer, 2018; Roe, 1999a), the main objective of the current work was to establish the initial validity of the SSQ. To do so, the first aim of the study was to evaluate the factorial validity of the strategic skills questionnaire. Therefore, it is expected that each item will load on its corresponding latent factor, that is, seven strategic skills (i.e., anticipating, scanning, connecting, goal setting, planning, monitoring, enacting) will represent seven different but related latent factors (Hypothesis 1). The second aim was to confirm whether the previously explored seven-factor solution is the best factorial solution. Hence, we expect that the seven-factor solution will yield the best fit, compared to other competing models (Hypothesis 2). The third aim was to explore the nomological network of the strategic skills through the study of the relationship between each strategic skills and other variables such as agentic general self-efficacy, learning goal orientation and performance goal orientation. Consistent with SCT (Bandura, 1986; Wood & Bandura, 1989), and empirical evidence (e.g., Bell & Kozlowski, 2002; Phillips & Gully, 1997), it is expected that strategic skills will be positively related with general self-efficacy (Hypothesis 3), and regarding goal orientation at work, it is expected that strategic skills will be positively associated with learning

goal orientation (Hypothesis 4a), but no associated with performance goal orientation (Hypothesis 4b).

3.3. Study 1: Questionnaire Development and Exploratory Factor Analysis

3.3.1. Method

3.3.1.1. Participants

The sample was composed by 253 individuals (M_{age} = 29, *SD* = 8) working in private (52 %), public (38 %), and mixed private-public ownership (10 %) organizations in France. Within this sample, 53.0 % were female, 29.2 % were male, and 17.8 % participants did not reply to the question. Regarding the educational background, 16.8 % of participants have a bachelor's degree, 68.3 % have a master's degree, 14.9 % have a doctoral degree. Concerning the organizational role, 32.7 % were interns (e.g., full-time trainees), 33.6 % were employees (e.g., analysts, staff), 23.1% were middle managers (e.g., supervisors, managers), and 3.4 % were top managers (e.g., CEO, vice-president). With respect to the size of the organization, 49.5 % of participants work for a large-sized (more than 250 employees) company, 20.7 % for a medium-sized (between 250 and 50 employees) company, 16.8 % for a small-sized (between 49 and 10 employees) company, and 13.0 % for a micro-sized (fewer than 10 employees) company.

3.3.1.2. Procedure

By using a convenience sampling of active employees in France, participants were invited to complete an online survey. Selected participants received an e-mail inviting them to participate in the study. Participants agreeing to respond voluntarily and anonymously, completed the questionnaire through an online survey platform where they were previously informed of the research goal, characteristics of the study, the estimated duration of the survey, and the names and contact details of the researchers.

3.3.1.3. Measure

Strategic skills. The questionnaire development process to measure strategic skills was the following: first, in accordance with agentic and proactive approaches (Bandura, 2018; Parker & Bindl, 2017), and action phases of the calendar model (Roe, 1999a), a pool of 42 items (6 items for each strategic skill) were either developed by us or adapted from measures (e.g., Bindl et al., 2012; Battistelli & Atzori, 2006; Battistelli et al., 2004; Parker & Collins, 2010; Ng, & Lucianetti, 2016) exploring strategic, agentic and/or proactive capacities/behaviors. Second, these items were sent to six organizational psychology researchers to evaluate their relevance, representativeness, and clarity. Based on the suggestions of experts, some items were reformulated and/or were excluded, thus resulting in a pool of 35 items (5 items for each strategic skill). Third, the reviewed version of the questionnaire was sent to 11 employees (i.e., three industrial engineers, three computer engineers, two economists, three accountants) working for private (n = 6) and public (n = 5) organizations as a pilot test, and to evaluate word clarity and the approximate time to complete the questionnaire. Last, after analyzing the feedback of the participants and the size and complexity of the questionnaire, a total of 28 items were evaluated but 1 item was removed because of no factor loading, thus resulting in a questionnaire comprising 27 items.

Consistent with our theoretical background, employees were asked to indicate at which level they consider themselves capable of performing a variety of reflective, decisional, and proactive job-related tasks and activities ("In my job, I am capable of …"). Designed to be used in an organizational setting, this questionnaire is an instrument developed to measure seven self-perceived capacities, named as strategic skills: anticipating (4 items; e.g., "Anticipating what I will have to do in the face of future events in my work"), scanning (3 items; e.g., "Analyzing how ongoing changes in my work context affect my work"), connecting (4 items; e.g., "describing how the different processes within my organization are interconnected"), goal

setting (4 items; e.g., “Setting challenging but achievable goals for myself”), planning (4 items; e.g., “Planning what needs to be done to ensure that my goals at work are achieved”), monitoring (4 items; e.g., “Monitoring whether the progress of the objectives is as planned”), enacting (4 items; e.g., “Carrying out the activities necessary to achieve the goals”). These items were measured through a five-point Likert format from 1 (“Never”) to 5 (“Every time”).

3.3.1.4. Data Analysis

An exploratory factor analysis (EFA) was performed to assess the factorial structure of the strategic skills questionnaire, by using Mplus 8.4 (Muthén & Muthén, 2017). Considering that the latent factors are supposed to be correlated, maximum likelihood extraction method (ML estimator) and an oblique (Geomin) rotation method were used in the analysis, following current methodological recommendations (Lloret et al., 2017; Zickar, 2020). It was used several indices to test the model goodness of fit such as Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI) whose values should be higher than .09, Root Mean Square Error of Approximation (RMSEA) along with the Standardized Root Mean Square Residual (SRMR) values lower than .08 (Bentler, 1990). Even though the significance of the chi-square (χ^2) value may produce a statistically significant result due to large sample size, it is also reported. Likewise, descriptive data are presented, and the reliability analysis was estimated with coefficient alpha and omega via JASP 0.14. Last, by using the Pearson’s r coefficient, bivariate analysis was performed to evaluate the degree of relationship among the different seven strategic skills.

3.3.2. Results

The appropriateness of the data for performing a factor analysis was tested before conducting our analysis. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.88 (Cerny & Kaiser, 1977) and the Bartlett’s Test of Sphericity was statistically significant ($p < .00$), thus indicating that our sample is suitable for the following analysis. Regarding the EFA, maximum

likelihood estimator and geomin rotation were used to determine the number of factors. Eigenvalues for sample correlation matrix (values above 1) along with all fit indices (see Table 3.1) suggest that the 7-factor solution (compared to other competing models) presents the best fit to the data, which is consistent with our theoretical framework proposing seven latent factors (strategic skills): anticipating, scanning, connecting, goal setting, planning, monitoring and enacting skills. Moreover, Table 3.2 presents the factor loadings of the 7-factor solution, thus showing that almost all the items loaded onto the corresponding hypothesized factors and appropriate levels of factor loadings. Hypothesis 1 is thus supported.

As part of our analysis, Table 3.3 presents descriptive and reliability statistics for each strategic skill and the internal consistency coefficients show adequate levels of reliability (e.g., ranging from $\omega = .72$ to $\omega = .89$). Moreover, as expected, the seven strategic skills were positively correlated among them, showing different statistically significant degrees of association (ranging from $r = .17$ to $r = .65$).

Table 3.1. *Model Fit Measures*

Model	χ^2	*df*	*p*	CFI	TLI	RMSEA	RMSEA 90% CI	SRMR	Model comparison	$\Delta\chi^2$	*df*	*p*
M1	2023.75	324	.00	0.52	0.48	0.14	0.14 - 0.15	0.12				
M2	1489.80	298	.00	0.66	0.60	0.13	0.12 - 0.13	0.09	M2-M1	533.95	26	.00
M3	1156.62	273	.00	0.75	0.68	0.11	0.11 - 0.12	0.07	M3-M2	333.17	25	.00
M4	806.51	249	.00	0.84	0.78	0.09	0.09 - 0.10	0.06	M4-M3	350.11	24	.00
M5	624.25	226	.00	0.89	0.82	0.08	0.08 - 0.09	0.04	M5-M4	182.26	23	.00
M6	431.88	204	.00	0.94	0.89	0.07	0.06 - 0.08	0.04	M6-M5	192.37	22	.00
M7	314.71	183	.00	0.96	0.93	0.05	0.04 - 0.06	0.02	M7-M6	117.17	21	.00

Note. $n = 253$. M1: 1 Factor, M1: 1 Factor, M2: 2 Factors, M3: 3 Factors, M4: 4 Factors, M5: 5 Factors, M6: 6 Factors, M7: 7 Factors

Table 3.2. *Seven-Factor Model: Exploratory Factor Analysis of the Strategic Skills Questionnaire*

Strategic Skill item	Factor loading						
	1	2	3	4	5	6	7
Factor 1: Anticipating skill							
ANT1	**.78**	−.01	−.03	.02	.03	−.01	.01
ANT2	**.71**	−.04	.03	.06	.05	.00	.00
ANT3	**.59**	.17	.02	−.04	−.06	.14	.01
ANT4	**.52**	.01	.03	.06	.11	−.06	−.01
Factor 2: Scanning skill							
SCA2	.16	.05	**.57**	−.17	−.04	.17	.04
SCA 3	−.03	.07	**.75**	.06	.08	.00	−.10
SCA 4	.04	.00	**.56**	.07	.02	−.05	.06
Factor 3: Connecting skill							
CON1	−.05	**.77**	.05	−.01	.04	−.02	.01
CON2	.03	**.70**	.01	.07	−.02	−.01	.05
CON3	−.02	**.84**	−.01	.02	.12	−.02	−.03
CON4	.07	**.76**	.04	−.06	−.07	.08	.02
Factor 4: Goal setting skill							
GOA1	.05	−.02	.04	**.40**	.05	.32	−.02
GOA2	.09	−.03	.03	**.52**	−.10	.35	.03
GOA3	.00	.03	−.10	**.96**	−.01	.00	.02
GOA4	.03	.01	.04	**.71**	.06	.07	.08
Factor 5: Planning skill							
PLA1	−.01	−.01	.08	.27	.24	**.49**	−.03
PLA2	.01	.06	−.11	.01	.05	**.78**	.00
PLA3	.01	.07	−.13	.01	.07	**.74**	.03
PLA4	.04	−.05	.06	.03	.03	**.62**	.11
Factor 6: Monitoring skill							
MON1	−.03	−.04	.05	−.10	**.86**	.08	.03
MON2	.01	−.01	.08	−.02	**.89**	−.04	.07
MON3	.07	.02	−.07	.06	**.69**	.09	−.01
MON4	.13	.08	−.15	.09	**.63**	.06	−.01
Factor 7: Enacting skill							
ENA1	.02	−.04	−.04	.04	.17	−.16	**.74**
ENA2	.07	.01	.01	−.16	−.01	.01	**.91**
ENA3	−.08	.02	.02	.02	.01	.17	**.64**
ENA4	−.05	.01	.01	.05	−.01	.05	**.76**

Note. $n = 253$. The extraction method was maximum likelihood with an oblique (Geomin) rotation. Factor loadings above .40 are in bold.

Table 3.3. *Descriptive Statistics, Reliability and Correlations of Strategic Skills*

Strategic Skill	*M*	*SD*	Reliability (ω)	1	2	3	4	5	6	7
1. Anticipating Skill	3.35	0.73	.79	(.79)						
2. Scanning Skill	3.29	0.84	.72	.29**	(.71)					
3. Connecting Skill	3.30	0.85	.87	.31**	.41**	(.87)				
4. Goal Setting Skill	3.72	0.78	.87	.47**	.15*	.17**	(.86)			
5. Planning Skill	3.72	0.83	.85	.36**	.22**	.26**	.61**	(.85)		
6. Monitoring Skill	3.72	0.84	.89	.36**	.17**	.28**	.49**	.65**	(.89)	
7. Enacting Skill	4.23	0.68	.86	.27**	.18**	.26**	.38**	.41**	.41**	(.86)

Note. $n = 253$; * $p < .05$; ** $p < .01$. *M* = mean; *SD* = standard deviation; Values in brackets are internal consistency reliability coefficients (Cronbach's alpha).

3.3.3. Discussion

In accordance with our first aim, the current findings showed that the underlying 7-factor structure of the strategic skills questionnaire is composed of seven different but related latent factors, in line with the theoretical skill framework (i.e., anticipating, scanning, connecting, goal setting, planning, monitoring, enacting) (Bandura, 2018; Gollwitzer, 2018; Roe, 1999a). This 7-factor structure, compared to other alternative models, showed preliminary evidence of the factorial validity as well as adequate levels of reliability of the questionnaire for measuring the strategic skills. In this way, the results of study 1, an exploratory but relevant phase of the measure development process, allow us to test the robustness of the model as well as their relationship to other agentic variables, in another sample and a confirmatory way (Zickar, 2020).

3.4. Study 2: Confirmatory Factor Analysis and Relationship with Other Agentic Variables

3.4.1. Method

3.4.1.1. Participants

292 employees (M_{age} = 36, *SD* = 10.20) of private (72.6 %), public (21.2 %), and mixed private-public ownership (6.2 %) organizations in France participated in the current study. The sociodemographic characteristic of the sample was the following: 38.7 % were female and 61.3 % were male. In terms of educational background, 4.8 % of respondents hold a bachelor's degree, 88.0 % a master's degree, and 7.2 % a doctoral degree. With respect to the organizational role, 6.5 % of surveyed participants were full-time interns, 49.7 % were employees (e.g., junior analyst, senior analyst), 31.8% were middle managers (e.g., supervisors, leads), and 12.0 % were top managers (e.g., CEO, vice-president). Last, regarding the size of the company of the respondents, 46.2 % among then work for a large-sized (more than 250 employees) company, 21.2 % for a medium-sized (50 to 250 employees) company, 13.4 % for

a small-sized (10 to 49 employees) company, and 19.2 % for a micro-sized (fewer than 10 employees) company.

3.4.1.2. Procedure

Data were collected from a large sample of active employees in France, by using an online crowdsourcing research platform: Crowdpanel. Given the interest in a sample of employees coming from a varied trained workforce in France, researchers decided to use this platform to recruit participants. Previous studies have shown that data gathered through online platforms (e.g., CrowdFlower, Mechanical Turk, Prolific Academic) can be comparable to conventional approaches as regards their diversity and quality (Newman et al., 2021; Walter et al., 2019). In order to ensure the quality of the data, we designed the study by following current recommendations (Newman et al., 2021; Porter et al., 2019), including predefined parameters of the essential characteristics of the sample (i.e., professional employees from Metropolitan France), time parameters (lower and upper) to complete the survey and the use of attention checks. The questionnaire was sent out to 300 employees (being properly informed of the research aim, characteristics, and the contact details of the researchers), but only 292 participants met the previously defined eligibility criteria.

3.4.1.3. Measures

Strategic skills. In the study 2, the seven strategic skills (i.e., anticipating, scanning, connecting, goal setting, planning, monitoring, enacting) were assessed by using the same items and specificities of the measure in the study 1 (i.e., question, items, response format).

Work goal orientation. We measured two forms of the goal orientation at work with the Boudrias et al.'s (2019) French version scale which evaluates learning goal orientation (5 items; e.g., "I often look for opportunities to develop new skills and knowledge"), and performance goal orientation (4 items; e.g., "I try to figure out what it takes to prove my ability

to others at work"). Items were assessed on a five-point Likert format from 1 ("Totally disagree") to 5 ("Totally agree").

General self-efficacy. The self-efficacy in its general form was measured using Scholz et al.'s (2002) scale which has been validated in more than 25 countries (including the French version) and assesses the self-perceived capacity to solve problems, unexpected situations and accomplish goals (10 items; e.g., "I am confident that I could deal efficiently with unexpected events"). Items were rated on a five-point Likert format from 1 ("Not at all true") to 5 ("Completely true").

3.4.1.4. Data Analysis

By using Mplus 8.4 (Muthén & Muthén, 2017) software, a confirmatory factor analysis (CFA) was performed to test the 7-factor structure of the strategic skills questionnaire, which was previously identified in the study 1. In accordance with our data analysis approach in the study 1 (Zickar, 2020), the same index criteria (CFI, TLI, RMSEA, SRMR, χ^2) was used to evaluate the model fit in the current study. Likewise, reliability and bivariate analysis were carried out using the same parameters of the study 1.

3.4.2. Results

Concerning the CFA, as can be seen in Table 3.4, the results showed that the hypothesized 7-factor correlated model (Model 1) presented adequate fit indices ($\chi2$ = 466.30; df = 303; p = 0.000; RMSEA = 0.043 [CI90% 0.04–0.05]; SRMR = 0.043; CFI = 0.96; TLI = 0.95), and the best fit to the data compared with other alternative models assuming a 6-factor models (Model 2 to Model 22) and a 1-factor model (Model 23). Moreover, as shown in Figure 3.1, the factor loadings of each item of the 7-factor model are greater than 0.63 and significant. These results provide supporting evidence for the hypothesis 2.

Table 3.4. *Model Fit Measures*

Model	χ^2	*df*	*p*	CFI	TLI	RMSEA	RMSEA 90% CI	SRMR	Model comparison	$\Delta\chi^2$	*df*	*p*
Model 1	466.301	303	.000	0.96	0.95	0.043	0.04 - 0.05	0.04				
Model 2	594.497	309	.000	0.93	0.92	0.056	0.05 - 0.06	0.05	Model 2 - Model 1	109.442	6	.000
Model 3	756.986	309	.000	0.89	0.87	0.070	0.06 - 0.08	0.09	Model 3 - Model 1	314.746	6	.000
Model 4	650.824	309	.000	0.91	0.90	0.062	0.06 - 0.07	0.06	Model 4 - Model 1	163.076	6	.000
Model 5	658.178	309	.000	0.91	0.90	0.062	0.06 - 0.07	0.06	Model 5 - Model 1	207.490	6	.000
Model 6	764.938	309	.000	0.88	0.87	0.071	0.07 - 0.08	0.08	Model 6 - Model 1	306.431	6	.000
Model 7	783.032	309	.000	0.88	0.86	0.072	0.07 - 0.08	0.10	Model 7 - Model 1	285.431	6	.000
Model 8	611.439	309	.000	0.92	0.91	0.058	0.05 - 0.07	0.06	Model 8 - Model 1	124.556	6	.000
Model 9	655.197	309	.000	0.91	0.90	0.062	0.06 - 0.07	0.07	Model 9 - Model 1	149.810	6	.000
Model 10	648.796	309	.000	0.91	0.90	0.061	0.06 - 0.07	0.07	Model 10 - Model 1	154.650	6	.000
Model 11	669.929	309	.000	0.91	0.89	0.063	0.06 - 0.07	0.07	Model 11 - Model 1	168.337	6	.000
Model 12	684.420	309	.000	0.90	0.89	0.065	0.06 - 0.07	0.09	Model 12 - Model 1	174.350	6	.000
Model 13	952.882	309	.000	0.83	0.81	0.084	0.08 - 0.09	0.12	Model 13 - Model 1	545.247	6	.000
Model 14	952.208	309	.000	0.84	0.81	0.084	0.08 - 0.09	0.10	Model 14 - Model 1	798.756	6	.000
Model 15	983.450	309	.000	0.83	0.80	0.086	0.08 - 0.09	0.08	Model 15 - Model 1	550.280	6	.000
Model 16	1165.546	309	.000	0.78	0.75	0.097	0.09 - 0.10	0.10	Model 16 - Model 1	981.050	6	.000
Model 17	581.521	309	.000	0.93	0.92	0.055	0.05 - 0.06	0.05	Model 17 - Model 1	93.012	6	.000
Model 18	740.315	309	.000	0.89	0.87	0.069	0.06 - 0.08	0.06	Model 18 - Model 1	255.735	6	.000
Model 19	846.229	309	.000	0.86	0.84	0.077	0.07 - 0.08	0.09	Model 19 - Model 1	357.159	6	.000
Model 20	668.835	309	.000	0.91	0.90	0.063	0.06 - 0.07	0.05	Model 20 - Model 1	170.297	6	.000
Model 21	937.190	309	.000	0.84	0.82	0.083	0.08 - 0.09	0.11	Model 21 - Model 1	417.520	6	.000
Model 22	973.752	309	.000	0.83	0.81	0.086	0.08 - 0.09	0.09	Model 22 - Model 1	471.183	6	.000
Model 23	2084.429	324	.000	0.55	0.51	0.136	0.13 - 0.14	0.11	Model 23 - Model 1	1210.51	21	.000

Note. n = 292; ANT: Anticipating; SCA: Scanning; CON: Connecting; GOA: Goal setting; PLA: Planning; MON: Monitoring; ENA: Enacting

Model 1: Hypothesized 7-factor model ANT+SCA+CON+GOA+PLA+MON+ENA; Model 2: 6-factor model (ANT+SCA)+CON+GOA+PLA+MON+ENA; Model 3: 6-factor model (ANT+CON)+SCA+GOA+PLA+MON+ENA; Model 4: 6-factor model (ANT+GOA)+SCA+CON+PLA+MON+ENA; Model 5: 6-factor model (ANT+PLA)+SCA+CON+GOA+MON+ENA; Model 6: 6-factor model (ANT+MON)+SCA+CON+GOA+PLA+ENA; Model 7: 6-factor model (ANT+ENA)+SCA+CON+GOA+MON+PLA; Model 8: 6-factor model ANT+ (SCA+CON)+GOA+PLA+MON+ENA; Model 9: 6-factor model ANT+(SCA+GOA) +CON+PLA+MON+ENA; Model 10: 6-factor model ANT+ (SCA+PLA)+CON+GOA+MON+ENA; Model 11: 6-factor model ANT+(SCA+MON) +CON+GOA+PLA+ENA; Model 12: 6-factor model ANT+ (SCA+ENA)+CON+GOA+PLA+MON; Model 13: 6-factor model ANT+SCA+(CON+GOA)+PLA+MON+ENA; Model 14: 6-factor model ANT+SCA+(CON+PLA)+GOA+MON+ENA; Model 15: 6-factor model ANT+SCA+(CON+MON)+GOA+PLA+ENA; Model 16: 6-factor model ANT+SCA+(CON+ENA)+GOA+PLA+MON; Model 17: 6-factor model ANT+SCA+CON+(GOA+PLA)+MON+ENA; Model 18: 6-factor model ANT+ SCA+CON+(GOA+MON)+PLA+ENA; Model 19: 6-factor model ANT+SCA+CON+(GOA+ENA)+PLA+MON; Model 20: 6-factor model ANT+SCA+CON+GOA+(PLA+MON)+ENA; Model 21: 6-factor model ANT+SCA+CON+GOA+(PLA+ENA)+MON; Model 22: 6-factor model ANT+SCA+CON+GOA+PLA+(MON+ENA); Model 23: 1-factor model (ANT+SCA+CON+GOA+PLA+MON+ENA)

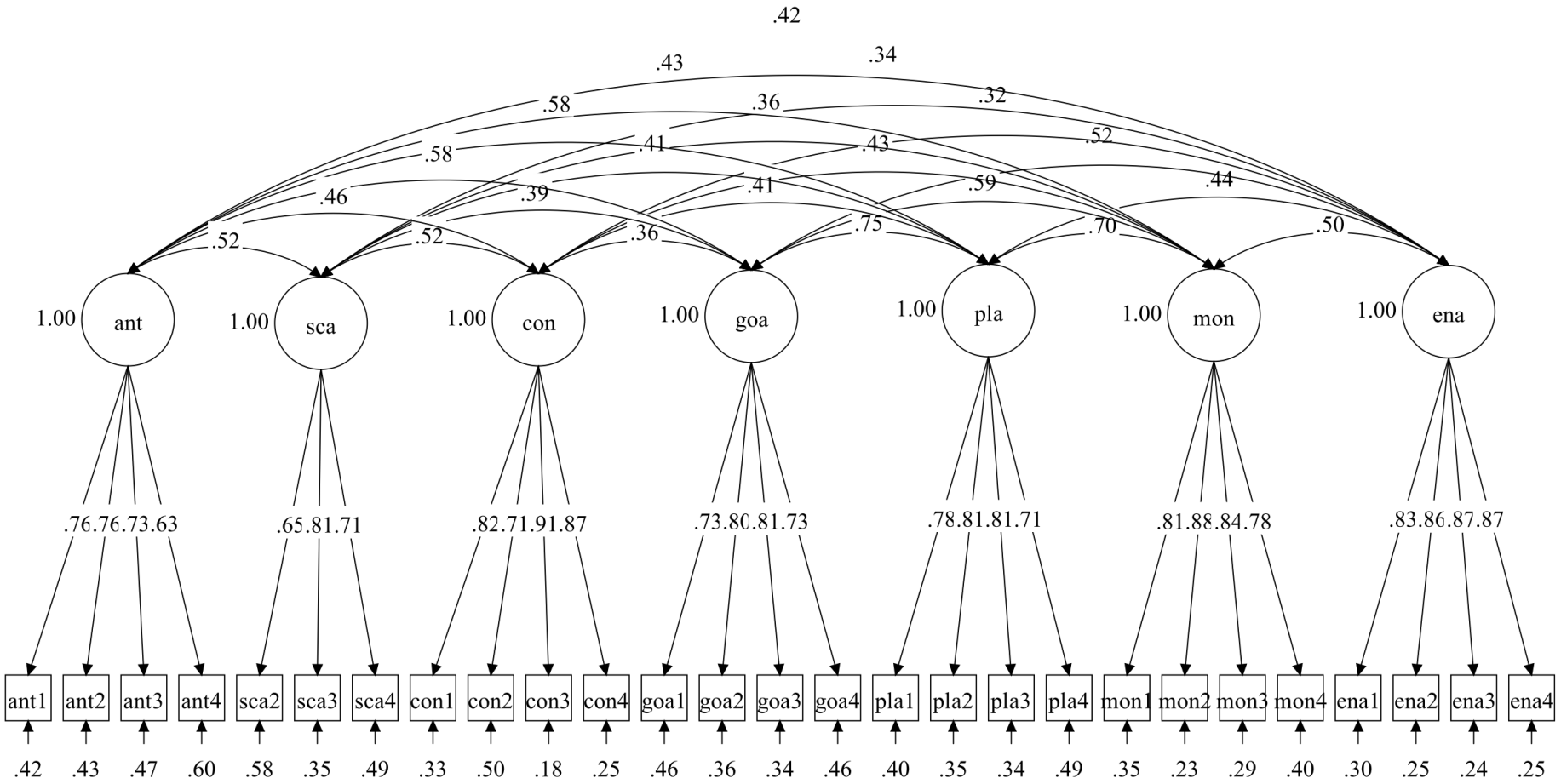


Figure 3.1. *Results of Confirmatory Factor Analysis of the Strategic Skills (n = 292)*

Note. ANT: Anticipating; SCA: Scanning; CON: Connecting; GOA: Goal setting; PLA: Planning; MON: Monitoring; ENA: Enacting

Table 3.5 presents descriptive, reliability and correlation statistics. Regarding reliability analysis, internal consistency reliability coefficients (McDonald's omega and Cronbach's Alpha), each factor of the strategic skill questionnaire showed satisfactory levels (e.g., ranging from ω = .76 to ω = .92). With respect to the correlation with other variables, as expected, there was a statistically significant positive relationship among the seven strategic skills and general self-efficacy (ranging from *r* = .33 to *r* = .55), thus supporting evidence for the hypothesis 3. Furthermore, while there was a statistically significant positive relationship among the seven strategic skills and learning goal orientation (ranging from *r* = .34 to *r* = .55), there was no statistically significant positive relationship between the strategic skills and performance goal orientation, except for the statistically significant positive but small relationship between the performance goal orientation and connecting (*r* = .16) and goal setting (*r* = .16) skills. Therefore, while hypothesis 4a is supported, and hypothesis 4b is partially supported. In this way, these findings lend evidence about the nomological validity of the strategic skills.

Table 3.5. *Descriptive Statistics, Reliability and Correlations of Study Variables*

Variables	*M*	*SD*	Reliability (ω)	1	2	3	4	5	6	7	8	9	10
1. Anticipating Skill	3.44	0.68	.81	(.81)									
2. Scanning Skill	3.29	0.78	.76	.52***	(.76)								
3. Connecting Skill	3.30	0.83	.90	.46***	.52***	(.90)							
4. Goal Setting Skill	3.66	0.77	.85	.58***	.39***	.36***	(.85)						
5. Planning Skill	3.60	0.80	.86	.58***	.41***	.41***	.75***	(.85)					
6. Monitoring Skill	3.67	0.80	.89	.43***	.36***	.43***	.59***	.70***	(.89)				
7. Enacting Skill	4.05	0.78	.92	.42***	.34***	.32***	.52***	.44***	.50***	(.92)			
8. Learning Goal Orie.	3.89	0.67	.85	.43***	.34***	.37***	.46***	.35***	.38***	.55***	(.85)		
9. Performance Goal Orie.	3.18	0.93	.84	.13	.04	.16*	.16*	.10	.06	.12	.34***	(.84)	
10. General Self-efficacy	3.63	0.55	.87	.46***	.33***	.34***	.55***	.42***	.36***	.40***	.64***	.30***	(.87)

Note. $n = 292$; * $p < .05$; ** $p < .01$; *** $p < .001$
M = mean; *SD* = standard deviation; Values in brackets are internal consistency reliability coefficients (Cronbach's alpha).

3.4.3. Discussion

Regarding our second aim, the results found in the CFA showed that the hypothesized 7-factor structure composed of 27 items grouped into seven theoretical factors (i.e.,

anticipating, scanning, connecting, goal setting, planning, monitoring, enacting) of the SSQ presents adequate fit indices, thus providing evidence about its factorial validity and appropriate levels of reliability. With respect to our third aim, as expected, bivariate analysis provides evidence about the nomological theoretical network of the strategic skills. In accordance to SCT (Bandura, 1986, 2018), these findings showed that the strategic skills were positively related with general self-efficacy and learning goal orientation, while no statistically significant relationship was found between the strategic skills and performance goal orientation, except for some cases, where a low positive correlation was found between performance goal orientation and connecting and goal setting skills.

3.5. General Discussion

Based upon the agentic approach of the SCT (Bandura, 1986, 2018) and action-regulation models (Gollwitzer, 2018; Roe, 1999a), the general purpose of the current work was developing and validating the SSQ, a measure exploring seven strategic skills (i.e., anticipating, scanning, connecting, goal setting, planning, monitoring, enacting) supporting the strategy-making process (from situational assessment to work-related action). As part of our analytical approach and the measurement development, two studies, having an exploratory and a confirmatory focus, were carried out in two different samples. In the light of the results of the studies 1 and 2, the SSQ showed adequate psychometric properties as regards is factorial validity (based on internal structure) and nomological validity (related to general self-efficacy, learning goal orientation, and performance goal orientation), as well as evidence concerning its reliability (based on alpha and omega and coefficients).

3.5.1. Theoretical Implications

From a theoretical standpoint, we consider that the current work offers four main contributions. First, while conventional approaches provide insightful elements of analysis to identify skills requirements in the digital edge, the current work proposes a view about those

capacities enabling strategy-making process, and consequently the human agency (Bandura, 2006). Based on an agentic approach (Bandura, 2018) and action-regulation models (Rubicon Model: Gollwitzer, 2018; Calendar Model: Roe, 1999a), the current work presents the conceptual development of the strategic skills, or skills allowing individuals not only to change themselves but also their changing environments, thus providing a complementary view of the proactive and reflective human action and development at work. Second, the current proposal raises the need to better understand capacities supporting the motivated human action at work. As many theories in motivation science (e.g., self-completion theory, mindset theory of action phases, theory of if-then planning; for a review see Gollwitzer, 2018) have pointed out, people move from intention to action through analyzing, establishing goals and planning their actions. Based on such psychological postulates, the strategic skills (i.e., anticipating, scanning, connecting, goal setting, planning, monitoring, enacting) are resources having the potential to help individuals to analyze an organizational issue and develop strategies to solve a work-related problem or to meet an organizational challenge. Third, the present work addresses how strategic skills are related with general self-efficacy as well as different forms of goal orientation at work such as learning and performance goal orientation at work, which is in line with social cognitive theory (Bandura, 1986) and considerable empirical evidence exploring work ability and other goal orientation variables (e.g., Bell & Kozlowski, 2002; Phillips & Gully, 1997; Porath & Bateman, 2006). These preliminary results provide insightful information about the nomological network of the strategic skills but also bring new possibilities to understand how these skills are related to other psychological mechanisms and workplace outcomes (in a direct and indirect way). Furthermore, consistent with the theoretical background (Bandura, 2006; Gollwitzer, 2018; Roe, 1999a), these strategic skills can be analyzed as a whole (e.g., by examining all strategic skills, or as situational appraisal and strategy implementation capacities) but also separately (e.g., by exploring how specific skills

are related – in a dynamic way – to specific phases of the motivated human action over time). Fourth, in a more complex (e.g., new market trends, economic crisis) and changing (e.g., new work environments, virtual teams) digital world of work, developing the individuals' capacity to create and implement effective strategies offers a new way to exert control over this growing technological-driven world.

3.5.2. Practical Implications

From the practical side, the present work makes two principal contributions. On the one hand, preliminary psychometric evidence (i.e., factorial validity, nomological validity, reliability) of the SSQP are provided. Designed to be used in an organizational setting, this work opens possibilities to evaluate further psychometric evidence by using specific organizational settings and cultural backgrounds. On the other hand, the SSQ joins a small but rising list of agentic capacity and behavioral measures (e.g., Bindl, 2012; Cenciotti et al., 2020; van Laar et al., 2018), thus offering an additional and complementary instrument for both organizational scholars and practitioners to evaluate and understand how these skills can be a source of human development and renewal at work. In this way, the development of the SSQ gives labor stakeholders the opportunity to draw their attention not only towards organizational requirements (e.g., technical, occupational) but also towards the human capacity to proactively adapt themselves and their environment.

3.5.3. Limitations and Future Research Avenues

The present work has certain noteworthy limitations which pave the way for future research. First, the preliminary psychometric evidence regarding the nomological validity was established by using a cross-sectional design and bivariate analysis (in two studies), thus showing the relationship between the strategic skills and self-efficacy and goal orientation at work. Therefore, further research must explore causal and dynamic relationship (e.g., through longitudinal studies) among strategic skills and other psychological dimensions. Second, future

studies are needed to explore not only self-perceived capacities (e.g., self-report) but also other indicators (e.g., supervisor report, situational judgment) to assess the strategic skills. Even though social cognitive theories have provided substantial evidence of how self-perceived capacities and self-regulation process are related to valuables learning processes and valuable behaviors at work (Sadri & Robertson, 1993), alternative measures can provide elements to unify process-based psychological approaches and work-related behaviors. Third, the human agency can be expressed in terms of agentic models more or less complex (Bandura, 2018; Gollwitzer, 2018), however, there is a need to expand the existing knowledge about how agentic capacities, and more specifically the strategic skills, can be developed by personal and contextual factors (e.g., antecedents), and/or how they are related to valuable workplace outcomes (e.g., consequents) in a more challenging and changing digital edge.

3.5.4. Conclusion

In times of rapid and profound changes in the world of work and organizations, particularly driven by the big current technological leap, building the workforce for a more and more challenging and complex work environment requires to developd not only technical and organizational capabilities, but also the individuals' capacity to adapt themselves and proactively transform their work environment (Battistelli & Odoardi, 2018; Bandura, 2018). In this regard, based on the agentic social cognitive theory (Bandura, 2018) and action regulation models (Gollwitzer, 2018; Roe, 1999a), we propose the conceptual bases and preliminary psychometric evidence of an instrument to measure strategic skills, or individuals' capacities supporting the agentic strategy-making process at work (from situational appraisal to strategy implementation) as a way to overcome the current and future challenges of an increasingly complex, changing and technology-driven workplace.

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Chapter 4

Enhancing Human Agency with Strategic Capacities at Work: Relationship Between Strategic Skills, Self-efficacy, and Individual Task Proactivity

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Chapter 4. Enhancing Human Agency with Strategic Capacities at Work: Relationship Between Strategic Skills, Self-efficacy, and Individual Task Proactivity

Abstract

The ongoing technological revolution at work is causing several and profound changes in organizations, thus impacting the way people perform their job and how they work with others. Though many efforts have been made to identify skills allowing people to use specific technologies or meet organizational demands, surprisingly, research has overlooked the potential of skills fostering the human agency by evaluating work environment and implementing effective strategies. Drawing from social cognitive theory, the present study examines how strategic skills, in the form of two higher-order strategy-making capacities, are related to individual task proactivity at work through self-efficacy. Data from a cross-sectional study carried out in a sample of active employees from different organizations in France (N = 522) was used to test our research model. Findings suggest that there are two-higher order strategic capacities (i.e., situational appraisal, strategy implementation), shaping seven specific strategic skills (i.e., anticipating. scanning, connecting, goal setting, planning, monitoring, enacting). Moreover, while the situational appraisal capacity – individual task proactivity relationship was partially mediate by self-efficacy, the relationship between strategy implementation capacity and individual task proactivity relationship was fully mediate by self-efficacy. The research and practical implications of strategic skills have for developing human agency are discussed.

Keywords: strategic skills, situational appraisal, strategy implementation, self-efficacy, proactivity

4.1. Introduction

An increasingly technological-driven world of work, also known as "Industry 4.0" or "Fourth Industrial Revolution", is changing several aspects of the organizational system (e.g., workplace environment, management) and of the people's work (e.g., work activities, team collaboration) (Battistelli & Odoardi, 2018; Parent-Rocheleau & Parker, 2021; Peña-Jimenez et al., 2021). In fact, some suggest that by 2030, around 20 million jobs can significantly change or disappear due to automation and robotics (Oxford Economics, 2019), and approximately 375 million people will need to change their careers as a result of the technological revolution (Manyika et al., 2017). In this scenario, many organizational scholars and practitioners have pointed out that skill development has become essential to transform this new technological revolution into an opportunity not only to attain technological mastery but also to allow people proactively manage a more interconnected and ever-changing work environment (e.g., Ackerman & Kanfer, 2020; Kanfer & Blivin, 2019; Parker & Grote, 2020; Odoardi et al., 2021). However, despite the impact that this rising fourth industrial revolution can have on how people feel, think, and behave at work (Landers & Marin, 2021; Murray et al., 2021), literature review suggests that technical, procurement and production issues have received more attention than the study of human capabilities or smart work, thus showing the clear need to further investigate this topic (for a review see Meindl et al., 2021).

Regarding skills research, some efforts have been made to identify the most important skills in the current technological revolution (for a review see Kipper et al., 2021; Peña-Jimenez, Antino, & Battistelli, 2021), which has allowed to take important steps in the theoretical and measurement development to evaluate some skill frameworks. Nevertheless, although most research – grounded on an organization-centered approach – focuses on the identification and development of several types of skills (e.g., digital, technical, occupational) to overcome specific organizational and occupational challenges (e.g., Dierdorff & Elligton,

2019; Van Laar et al., 2018), more research – based on a human-centered approach – is needed to evaluate skills allowing individuals to develop human agency at work (e.g., situational assessment, strategic planning) and, more importantly, how these are related to valuable behaviors at work (Bandura, 2018; Cenciotti et al., 2020). Accordingly, in a more uncertain and interconnected work environment which requires not only technical proficiency but also proactive behaviors at work, research on the individuals' capacity not only to use tech devices but also to manage and transform their environment is even more relevant to better understand and foster human development and renewal at work (e.g., Bandura, 2018, 2019; Dachner et al., 2021; Yoon, 2019).

From a psychological perspective, "Human agency" is a term used to refer to the general capacity to exercise control over the environment as well as the quality of one's life, which is characterized by different functional consciousness core properties: forethought (i.e., envisioning future scenarios), self-reactiveness (i.e., adopting and implementing action plans), and self-reflectiveness (e.g., examining and monitoring their capacity and actions) (Bandura, 2001, 2018). Based on such premises, developing the human agency is central to allow individuals become effective fore-thinkers, planners and self-examiners to operate within a broad network of challenging and changing social scenarios (Bandura, 2018). Nevertheless, in times of major social and labor changes, the debate on the nature of the human agency as well as its importance to address some of the most important social and organizational challenges has significantly increased in recent years (e.g., Bandura, 2018, Hirst et al., 2020; Yanchar, 2021, Yoon, 2019). For example, Yanchar (2021) stresses the importance of identifying the nuances in the different theoretical visions of human agency which can be explained, for instance, through two different but complementary approaches: a concern-oriented (i.e., action as a result of concerns or the sense of mattering) and a control-oriented (i.e., any form of action aimed at exerting some control over a situation) approach. These theoretical differences also

pose the need to appropriately distinguish the unique general capacity to control the environment from those personal resources explaining and/or developing such general human agency (e.g., Cenciotti et al., 2020; Yanchar, 2021).

In this regard, from an organizational perspective, recent studies have proposed theoretical frameworks and instruments to evaluate the mechanisms or capacities related to the human agency at work (e.g., Cenciotti et al., 2020; Yoon, 2019). For instance, grounded on central properties of human agency, Yoon (2011) proposes to evaluate the intentionality, forethought, self-reactiveness and self-reflectiveness. Another proposal, grounded on a proactive regulation model, poses the importance of exploring envisioning, reflecting, planning, and enacting behaviors at work (Bindl et al., 2012). Later, Cenciotti et al. (2020) propose to examine forethought, self-reflection, self-regulation and vicarious as related capacities. More recently, Peña-Jimenez et al. (2021a) have proposed to evaluate the strategic skills (i.e., anticipating, scanning, monitoring, goal setting, planning, monitoring, enaction) supporting the strategy-making process (i.e., situational appraisal, strategy implementation) as a way to improve the human agency, or the capacity to control the environment. Nevertheless, while the relationship between these capacities and the self-efficacy (as a central psychological mechanism related to the human agency) has been extensively studied separately, studies evaluating how these capacities (collectively) are related to relevant organizational outcomes (e.g., proactivity) are still necessary to better understand and determine how they contribute to developing agency at work (e.g., Bindl et al., 2012; Cenciotti et al., 2020; Montani et al., 2015).

To fill this gap, drawing from the human agency approach of the social cognitive theory (Bandura, 2006, 2018), the current work examines how strategic skills (Peña-Jimenez et al., 2021a), acting as a situational assessment capacity (i.e., anticipating, scanning, monitoring) and strategy implementation capacity (i.e., goal setting, planning, monitoring, enaction), are related to individual task proactivity at work, through the general self-efficacy as a central

psychological mechanism of the human agency. Considering that we use a recently developed skill framework (named as strategic skills; Peña-Jimenez et al., 2021a), the current work makes two relevant contributions to the human agency literature. On the one hand, we provide preliminary empirical evidence about how strategic skills, in the form of two higher-order strategy-making capacities, are related to work performance, and more specifically individual task proactivity at work. On the other hand, we explored the role of self-efficacy (a central mechanism of human agency), as a mediator of the relationship between strategic skills as the form of higher-order strategic capacities and proactive work behaviors. Thus, in times of several and rapid changes due to the current technological revolution, strategic skills open up new opportunities to understand and develop the human agency at work.

4.2. Theoretical Background and Hypotheses

Social cognitive theory (SCT; Bandura, 2001, 2018), posits that, as part of their human nature, people are not just passive actors but rather proactive and reflective agents. In the same vein, many other agentic (or non-mechanistic) psychological theories (for a review see Kanfer et al., 2017; Yanchar, 2021) highlight that the individuals' actions are the result of cognitive, affective and motivational processes aimed at exerting "control" over their life and their environment. Consistent with the above, many scholars (e.g., Bandura, 2018; Gollwitzer, 2018; Locke & Latham, 2019) agree the goal concept can be a key tool to understand how humans transform an intention into an action, as has been explained for example by the self-regulation process which describes three different but interrelated set of activities (i.e., self-regulation process): 1) Self-monitoring which is the attention that people give to behaviors and events related to the goal, 2) Self-evaluation is the judgment of the current state of the goal as well as goal progress, and 3) Self-reaction which denotes an individual's response as an evaluation between desired and goal states (Kanfer et al., 2017).

These assumptions of the human agency have taken the form of different action-phases models such as the Calendar model (Roe, 1999a; i.e., generating, filtering, scheduling, preserving, enactment), and the Rubicon model (Gollwitzer, 2018; i.e., pre-decisional, pre-actional, actional, post-actional) which explain the psychological self-regulation process (from situational analysis to goal achievement) as well as different personal mindsets (i.e., deliberative, implemental). In the organizational context, this human capacity to solve a problem or attain a goal at work has taken the form of the strategy-making process; that is, situation appraisal and diagnosis, strategic option generation, strategic selection, and strategy enactment, which requires a set of personal resources allowing people evaluate their surrounding environment as well as developing and executive strategies (Grant & Baden-Fuller, 2018). Thus, in a volatile, uncertain, complex, and ambiguous world of work, fostering the individuals' capacity to control their environment by thinking and implementing effective strategies acquires a special relevant, especially for organizational leaders (Bennett & Lemoine, 2014; Rimita et al., 2020). For instance, Goldman and Scott (2016) suggest that capacities such as visioning, environmental awareness, assessment and evaluation, strategy creation, planning, implementation, and organizational alignments are essential for the strategic thinking competency. In the present study, we therefore evaluate how strategic skills in the form of the two higher-order capacities (i.e., situational appraisal, strategy implementation) are related to individual task proactivity through the mediating process of the self-efficacy.

4.2.1. Strategic Skills as Situational Appraisal and Strategy Implementation Capacities

Strategic skills are defined as the individuals' capacities allowing strategy-making process (from situational appraisal to strategy implementations), which are characterized through the following skills: anticipating (i.e., envisioning future organizational scenarios or possible outcomes), scanning (i.e., searching for events having an impact to the attain goals), connecting (i.e., linking objects and/or events to identify how organization works), goal setting

(i.e., defining challenging but feasible targets), planning (i.e., developing an action plan to achieve a stated goal), monitoring (i.e., controlling whether defined plan progresses as expected), and enacting (i.e., committed preliminary actions to implement the action plan) (Peña-Jimenez et al., 2021a). Even though strategic skills are different capacities which go together with different stages of the motivated human action, these also share similar functionalities of the intricate strategy-making process. In other words, while some skills such as anticipating, scanning and connecting are capacities oriented to make an appropriate "situational appraisal", other skills such as goal setting, planning, monitoring, and enacting are capacities oriented to the "strategy implementation". Here is presented the theoretical background and research evidence explaining the nature and importance of these two supra-capacities (i.e., situational appraisal, strategy implementation), which would act as a functional set of drivers to foster agentic human behavior.

Conceptual development and empirical evidence on general mental ability have shown that there are different and related forms of capacities such as emotional intelligence (e.g., Goleman, 1995), social intelligence (e.g., Kihlstrom & Cantor, 2000), and practical intelligence (e.g., Lievens & Chan, 2010), explaining how people approach and solves a problem in different environments. However, it has also been demonstrated that there are underlying higher order capacities (or supra-capacities) that explain complex cognitive processes, as shown the general mental capacity or g factor (e.g., Funke, 2010; Reeve & Hakel, 2002). According to McGrew (2009), there is at least three levels or forms of cognitive abilities, that is, the g-factor is a general ability placed at the highest level of mental ability (i.e., Stratum III), which in turn shapes approximately 10 broad mental abilities (i.e., Stratum II), and at the lowest level, it is possible to identify many narrow and essential mental abilities (i.e., Stratum I). For example, in the educational context, complex problem solving has been defined and measured as a general capacity that can be explained through two broad capacities (i.e., knowledge

acquisition, knowledge application), and many other basic cognitive operations and knowledge (Funke, 2001; Greiff et al., 2013). In the same vein, skills such as self-emotion appraisal, other's emotion appraisal, use of emotion, and regulation of emotion have been explained through a higher-order factor labeled as emotional intelligence (Iliceto & Fino, 2017; Wong & Law, 2002). This brings to light that the human capacity to overcome the challenges at work can be explained through specific skills (e.g., strategic skills) but also through higher-order capacities (e.g. situational assessment, strategy implementation) sharing common ground in complex mental process.

In the organizational setting, research on work ability (e.g., for a review see Brady et al., 2020) has also extensively studied and provided evidence on how physical and/or mental abilities allow individuals meet the requirements in their workplace. Nevertheless, although this general construct, named work ability, has succeeded in explaining how this broad capacity is related to different key personal and context antecedents (e.g., job demands, job resources) and outcomes (e.g., job attitudes, job performance) at work (Brady et al., 2020; McGonagle et al., 2015), there is also considerable empirical evidence showing that this general ability at work consists of different capacities as it has been shown through different objective and perceive work ability measures (e.g., Brady et al., 2020, Ilmarinen et al., 1991a; Martus et al., 2010). In fact, the different ways in which this construct has been measured (e.g., work ability index: Ilmarinen et al., 1991a; work ability survey-revised: Noone et al., 2014) has shown that even though there are different capacities (e.g., health, physical, mental) allowing employees be able to do their job, it is also possible to explain this work ability by a general or supra-dimensional capacity (Brady et al., 2020; Ilmarinen et al., 2015). Moreover, meta-analytical research (Brady et al., 2020) has found that this general ability at work is positively related to job attitudes (r = .26), job performance (r = .32), and work motivation (r = .30), while it is negatively associated with job strain (r = –.40), exit intentions (r = –.26) and exit behaviors (r = –.26) at work.

Therefore, examining how specific skills act together or are shaped by supra-dimensional or higher order capacities can allow us to understand their relationship not only with human agency (i.e., self-efficacy) but also with valuable work outcomes (e.g., proactive work behaviors).

Regarding strategic skills (Peña-Jimenez et al., 2021a), we consider that the strategic skills (i.e., anticipating, scanning, connecting, goal setting, planning, monitoring, enacting) allow individuals to address specific cognitive requirements of the strategy-making process, but at the same time, these skills represent particular forms of two higher-order capacities: situational appraisal and strategy implementation. According to our theoretical background (Bandura, 2018; Gollwitzer, 2018; Roe, 1999a), solving a problem can be explained through two phases representing complex mental processes: a "pre-decisional or deliberative phase" which is responsible of gathering information to make an appropriate evaluation before to make a decision, followed by an "implemental or post-decisional phase" which is oriented to develop and adopt the strategy to deal with the challenges and size the opportunities to meet goals (Gollwitzer, 2018; Roe, 1999a). Thus, we posit that the "situational appraisal" capacity is a higher-order capability allowing people make an overall assessment of their surrounding context (e.g., potential changes, envision future scenarios, understanding how a dynamic social system works) (Gollwitzer, 2018; Grant & Baden-Fuller, 2018), thus shaping anticipating, scanning, and connecting skills. In addition, we argue that the "strategy implementation" capacity is another higher-order capability allowing individuals to be able to prepare and execute the strategy to meet the goal (Gollwitzer, 2018; Grant & Baden-Fuller, 2018), in other words, designing goals, developing, monitoring and implement plans, thus shaping goal setting, planning, monitoring and enacting skills.

Taking as reference the notion of Stratum (McGrew, 2009), we argue that strategic skills represent essential capacities placed in the core of the strategy-making process (i.e., Stratum I),

representing two broad forms of higher-order level deliberative (i.e., situational assessment) and implemental (strategy implementation) capacities of a complex mental process (i.e., Stratum II). In the same vein, by using the mindset notion, Gollwitzer (2018) states that the cognitive procedures associated with solving a given task can be explained through different mindsets: deliberative (e.g., processing environmental information to set a goal) and implemental (e.g., planning how to attain a goal), thus suggesting that these strategic skills can be explained through two different but related supra-capacities. Moreover, in accordance with the calendar model (Roe, 1999a), the personal resources related to the different phases of the motivated human action can be explored by focusing in a specific goal or task, which can be useful for purposes of theoretical development; nevertheless, in the real organizational world, people face several demanding, changing and even competing goals at the same time, which makes difficult to explore those skills separately. For this reason, evaluating higher-order capacities allows us to understand how these supra-capacities help employees face multiple tasks and duties within the organizational context.

Following this logic, we argue that strategic skills can be displayed in two different capacities deliberative and implemental capacities (Peña-Jimenez et al., 2021a). Put another way, on the one hand, considering that anticipating, scanning and connecting are skills exploring and processing information for a better understanding of the organizational environment, all together can act together or are shaped by a situational appraisal (deliberative) capacity. On the other hand, goal-setting, planning, monitoring ang enacting are skills representing the strategy implementation (implemental) capacity. Thus, we hypothesized the following:

Hypothesis 1: Anticipating, scanning and monitoring skills will load on a higher order factor representing the situational appraisal capacity.

Hypothesis 2: Goal setting, planning, monitoring and enacting skills will load on a higher order factor representing the strategy implementation capacity.

4.2.2. Strategic Capacities and Proactivity at Work

Skills are considered an essential personal asset to successfully face challenges at work (Brady et al., 2020; Campbell & Wiernik, 2015; Kurz & Bartram, 2002), especially in the current technological revolution (Ackerman & Kanfer, 2020; Kanfer & Blivin, 2019). Previous meta-analysis studies have shown that different (e.g., cognitive, social, psychomotor) skills, along with other variables such as previous performance on related jobs and job knowledge, are good predictors of job performance (e.g., Brady et al., 2020; Carpini et al., 2017; Hunter & Hunter, 1984). Employee performance is considered one of the most valuable workplace outcomes fostered by distal variables such as job skills (e.g., Campbell & Wiernik, 2015; Motowidlo & Kell, 2012; Parker et al., 2010; Tornau & Frese, 2013) and proximal predictors, like self-efficacy and intrinsic motivation (e.g., Ozyilmaz et al., 2018; Parker et al., 2010).

Skill research has provided substantive empirical evidence on how a large number skills are relevant to many work outcomes, for example, a set of specific intrapersonal (i.e., how people control themselves in given social contexts) and interpersonal (how individuals interact with others at work) skills, also known as soft skills, has proven to be positively associated with job performance (e.g., Ibrahim et al., 2017; Yun & Lee, 2017), innovation at work (e.g., Hendarman & Cantner, 2018), and more importantly, key resources for entrepreneurs success (e.g., Baron & Markman, 2000; Baron & Tang, 2009). Likewise, regarding strategic skills (Peña-Jimenez et al., 2021a), many skills such as metacognitive assessment skills, forecasting skills, solution construction and evaluation skills, and planning and implementation skills have demonstrated to be positively correlated with performance at work (e.g., Byrne et al., 2010; Antes & Mumford, 2012; Marshall-Mies et al., 2000; Mumford et al., 2017). Nevertheless, while cumulative research evidence has shown how personal resources (e.g., knowledge, skills,

abilities) are related to task proficiency performance (e.g., Brady et al., 2020; Hunter & Hunter, 1984), a rising line of research has stated the importance of examining different forms of work performance such as task proactivity at work (Griffin et al., 2007; Parker et al., 2010; Roberge & Boudrias, 2021), as an alternative view of how people pursue a proactive pathway to meet a goal by transforming their work environment (Parker et al., 2010).

Individual task proactivity refers to the extent to which employees adopt future-oriented and self-starting behaviors to change themselves or their work environment to achieve effective outcomes at work, which is considered a complementary but important form of other work role behaviors such as individual task proficiency and adaptivity (Griffin et al., 2007). Considering that organizations are facing unexpected and rapid changes in the current technological revolution, in the present study we focus on proactive performance since these are future-directed and self-starting behaviors to deal with a more changing and challenging work environment (Griffin et al., 2007; Ployhart & Bliese, 2006). Unlike other related constructs (e.g., "individual initiative", "conscientious initiative") related to concern, effort and persistence, in this paper, individual task proactivity is a broad evaluation of how employees identify opportunities and adopt behaviors to implement changes in an active and engaged way, taking different forms such as taking charge, voice, and innovative work behaviors (Griffin et al., 2007).

From a theoretical perspective (Bandura, 2006, 2018), we consider that the two higher-order strategic capacities (i.e., situational assessment, strategy implementation), shaping the strategic skills (i.e., anticipating, scanning, connecting, goal setting, planning, monitoring, enacting), represent individuals' agentic supra-capacities oriented to exert control over their environment in an active way. Empirically, this conceptual link between skills (e.g., problem solving, general mental ability) and proactive behaviors have been established in some meta-analytical studies (e.g., Thomas et al., 2010; Tornau & Frese, 2013). In this regard, previous

studies have examined how these skills are positively related to proactive behaviors at work. For example, by using a goal-regulatory framework, Montani et al. (2015) have found a positive relationship between envisioning, planning and innovative work behavior, which is consistent with Bindl et al., (2012)'s findings that proactivity at work can be explained through a complex regulation process which requires different skills to foster envisioning, reflecting, planning and enacting. Consistent with the above, it is therefore possible to posit that these strategic capacities can be positively related to proactive performance since future-focused, change-oriented and self-initiated are three core properties of proactive behaviors (Parker & Collins, 2010; Parker & Liao, 2016), as hypothesized below.

Hypothesis 3. Situational appraisal capacity will be positively related to individual task proactivity.

Hypothesis 4. Strategy implementation capacity will be positively related to individual task proficiency.

4.2.3. Self-efficacy as a Key Psychological Mechanism of Human Agency

Self-efficacy is defined as the individual's belief about his or her capacity to perform a task (Bandura, 1986). According to SCT (Bandura, 2006, 2018), self-efficacy represents a key mechanism of the self-regulation process allowing individuals move from an intention (i.e., establishing a work-related goal) to an action (i.e., goal-oriented behaviors), which is also considered a core psychological mechanism of the human agency. In organizational setting, self-efficacy refers to the individual's self-perceived capacity to successfully perform work-related tasks or competent to deal with organizational demands (Bandura, 2001; Ventura et al., 2015). In other words, people showing high levels of self-efficacy may tend to interpret complex situations or problems at work as challenges which can be solved by using their personal resources such as skills (Bandura, 1986, 2001). Psychological research has provided substantial evidence of the mediating role (a regulatory mechanism) of self-efficacy in the

relationship between personal capacities (e.g., skills, knowledge) and work performance (e.g., task proficiency and proactivity) (e.g., Parker et al., 2010; Tornau & Frese, 2013; Stajkovic & Luthans, 1998; Wood et al., 1990). For instance, meta-analytical evidence has demonstrated that self-efficacy mediates the relationship between personal capacities (e.g., cognitive ability) and work-related performance (Carpini et al., 2017; Chen et al., 2001; Judge et al., 2007).

Empirical evidence also suggests that, on the one hand, self-efficacy can be developed through enactive mastery experience, vicarious experience, verbal persuasion, and physiological and psychological reactions (Bandura, 1986, 2001). This means that, among the many personal factors boosting self-efficacy, a large number of skills (e.g., critical thinking, political) constitute an important individual asset to develop the sense of mastery in complex and changing environments (e.g., Gloudemans et al., 2013; Jawahar et al., 2008). On the other hand, self-efficacy is positively related to some organizational outcomes like work performance (Judge et al., 2007; Stajkovic & Luthans, 1998). For instance, many proactive scholars (Parker et al., 2006; Sonnentag & Spychala, 2012) have shown that self-efficacy is positively associated with proactive work behaviors.

From these findings, we consider that personal resources such as strategic skills in the form of higher-level strategic capacities may contribute not only to a sense of mastery but also to the people's belief that they can transform their work environment in a proactive way. Indeed, the individual can develop knowledge, skills and other abilities in order to perform a task, however, the individual's action is not always an automatic response, but rather a reasoned or planned behavior which will depend upon the self-regulation process. Therefore, we expect that self-efficacy act as the psychological mechanism which will integrate the individual's capacities and work-related action, for example, task proactivity.

Hypothesis 5. Situational appraisal capacity will be positively related to individual task proactivity through self-efficacy.

Hypothesis 6. Strategy implementation capacity will be positively related to individual task proficiency through self-efficacy.

4.3. Method

4.3.1 Participants

522 employees (M_{age} = 33, *SD* = 10) working in different private (65 %), public (28 %) and mixed private-public ownership (7 %) companies in France participated in the present study. Among these participants, 51 % were male and 49 % were male. With respect to their educational background, 13.4% of employees hold a bachelor's degree, 76.6 % hold a master's degree, and 10.0 % have a doctoral degree. Regarding the organizational role in their organizations, 16.7 % were full-time interns, 45.0 % were front-line employees (e.g., junior and senior analysts), 29.5 % were middle managers (e.g., coordinators, managers), and 8.8 % were top managers (e.g., CEO, CFO, COO). As regards the size of their company, the majority (46.7 %) of the participants work for a large-sized (more than 250 workers) organization, followed by 21.5 % of the participants working for a medium-sized (between 250 and 50 workers) organization, 15.3 % for a small-sized (between 49 and 10 workers) company, and 16.5 % for a micro-sized (fewer than 10 workers) organization.

4.3.2. Procedure

Designed as a cross-sectional study (Spector, 2019), data were collected through a convenience sampling of employees in metropolitan France. Employees were invited to participate in the present study, being previously informed about the goal, characteristics of the study, the approximate duration of the survey, and the contact details of the research team responsible of the present study. Employees agreeing to participate in the study, voluntarily and anonymously respond the survey through an online platform.

4.3.3. Measures

Strategic capacities. The two strategic higher-order capacities were measured by using the French version of the strategic skills questionnaire, composed of twenty-seven items and adapted to the organizational context (Peña-Jimenez et al., 2021a). Participants were expected to indicate at which extent they consider themselves capable of performing different tasks and activities at work ("In my job, I am capable of …"). The situational assessment higher-order capacity was assessed through 11 items referring the following strategic skills: anticipating (e.g., "Anticipating what I will have to do in the face of future events in my work"), scanning (e.g., "Analyzing how ongoing changes in my work context affect my work"), and connecting (e.g., "describing how the different processes within my organization are interconnected"). The strategy implementation higher-order capacity was measured by using 16 referring the following strategic skills: goal setting (e.g., "Setting challenging but achievable goals for myself"), planning (e.g., "Planning what needs to be done to ensure that my goals at work are achieved"), monitoring (e.g., "Monitoring whether the progress of the objectives is as planned"), enacting (e.g., "Carrying out the activities necessary to achieve the goals"). Items were rated by using a five-point Likert format from 1 ("Never") to 5 ("Every time").

General self-efficacy. Validated in many languages and cultural backgrounds (including the French version), the self-efficacy was measured in its general form through the Scholz et al.'s (2002) ten-item scale which assesses the individual's belief regarding her/his capacity to overcome problems, unexpected events, and meet goals. (e.g., "I am confident that I could deal efficiently with unexpected events"). Regarding items rating, participants were expected to rate on a five-point Likert format from 1 ("Not at all true") to 5 ("Completely true").

Individual task proactivity. We measured the individual task proactivity by using a French translation (Chiocchio et al., 2012) of the Griffin et al.'s (2007) three-item scale which assess future-oriented, changed-focused and self-starting behaviors at work (e.g., "Come up

with ideas to improve the way in which your core tasks are done") composed of 3 items. Participants were asked to rate how often they displayed proactive behaviors in their work-related tasks in the previous three months, through a five-point Likert format from 1 ("very little") to 5 ("great deal").

4.3.4. Data Analysis

As part of our analytical approach, Structural Equation Modeling (SEM) was carried out to evaluate the hypothesized factorial structure (measurement model) and the relationship between study variables (structural model), with Mplus 8.4 (Muthén & Muthén, 2017). The theoretical model was also compared to other alternative models. Different fit indices were used to assess the robustness of the model as follows: Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR) values were expected to be lower than .08 (Bentler, 1990), and Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI) were expected to show values higher than .09. Given the large sample size, chi-square (χ^2) value may produce a statistically significant, but it is also reported. Descriptive data and bivariate analysis were performed with Statistical Package for Social Sciences software version 25.0, and reliability analysis (exploring Cronbach's alpha and McDonald's omega) was conducted through JASP software version 0.14.1.

4.4. Results

4.4.1. Measurement Model

Findings showed that the underlying items load on their corresponding latent factor, in accordance with our hypothesized research model ($\chi2(727) = 1397.18$, $p < .05$; CFI = 0.93; TLI = 0.93; RMSEA = 0.04 [CI90% 0.04–0.05], SRMR = 0.05). As shown in Table 4.1, the theorized 11-factor solution of our model yielded the best fit to the data (i.e., 2 second-order factors: situational assessment and strategy implementation capacities; 7 first-order factors: anticipating, scanning, connecting, goal setting, planning, monitoring, and enacting skills;

general self-efficacy; individual task proactivity). Furthermore, in comparison with other alternative models, the theorized 11-factor solution displayed better fit indices, thus showing that the situational assessment capacity was modeled as a higher-order latent variable composed of anticipating, scanning and connecting skills as lower-order latent variables, and the strategy implementation capacity was modeled as a higher-order latent factor composed of goal setting, planning, monitoring and enacting skills as lower-order latent factors. Hypotheses 1 and 2 are therefore supported. Table 4.2 presents descriptive and reliability statistics for the different study variables, and as can be noted, the internal consistency coefficients showed appropriate levels of reliability (e.g., ranging from $\omega = .74$ to $\omega = .90$). Furthermore, regarding the bivariate analysis, the different study variables were positively associated with each other, showing statistically significant degrees of association (ranging from $r = .21$ to $r = .86$).

Table 4.1. *Model Fit Measures*

Model	χ^2	*df*	CFI	TLI	RMSEA	RMSEA 90% CI	SRMR	Model comparison	$\Delta\chi^2$	Δ *df*
1. Hypothesized 11-factor model	1397.18*	727	0.93	0.93	0.042	0.04 - 0.05	0.051			
2. Model A (10-factor model)	1458.00*	730	0.93	0.92	0.044	0.04 - 0.05	0.057	2 vs. 1	54.57*	3
3. Model B (10-factor model)	2042.40*	730	0.86	0.86	0.059	0.06 - 0.06	0.062	3 vs. 1	467.86*	3
4. Model C (9-factor model)	2096.23*	732	0.86	0.85	0.060	0.06 - 0.06	0.067	4 vs. 1	527.05*	5
5. Model D (3-factor model)	4270.57*	737	0.64	0.61	0.096	0.09 - 0.10	0.088	5 vs. 1	1557.98*	10
6. Model E (2-factor model)	4897.46*	739	0.57	0.55	0.104	0.10 - 0.11	0.094	6 vs. 1	1942.81*	12
7. Model F (2-factor model)	5033.97*	739	0.56	0.53	0.106	0.10 - 0.11	0.098	7 vs. 1	1935.95*	12
8. Model G (2-factor model)	4935.44*	739	0.57	0.54	0.104	0.10 - 0.11	0.095	8 vs. 1	1941.76*	12
9. Model H (1-factor model)	5664.21*	740	0.49	0.46	0.113	0.11 - 0.12	0.104	9 vs. 1	2216.84*	13

Note. n = 522; * p < .01; SIT: situational appraisal; STR: strategy implementation; ANT: anticipating; SCA: scanning; CON: connecting; GOA: goal setting; PLA: planning; MON: monitoring; ENA: enacting; GSE: General self-efficacy; ITP: Individual task proactivity.

Hypothesized 11-factor model: 2 second-order factors (i.e., SIT, STR) + 7 first-order factors (i.e., ANT, SCA, CON, GOA, PLA, MON, ENA) + GSE + ITP; Model A (10-factor model): 1 second-order factor (i.e., SIT + STR) + 7 first-order factors (i.e., ANT, SCA, CON, GOA, PLA, MON, ENA) + GSE + ITP; Model B (10-factor model): 2 second-order factors (i.e., SIT, STR) + 7 first-order factors (i.e., ANT, SCA, CON, GOA, PLA, MON, ENA) + (GSE + ITP); Model C (9-factor model): 1 second-order factor (i.e., SIT + STR) + 7 first-order factors (i.e., ANT, SCA, CON, GOA, PLA, MON, ENA) + (GSE + ITP); Model D (3-factor model): (ANT + SCA + CON + GOA + PLA + MON + ENA) + GSE + ITP; Model E (2-factor model): (ANT + SCA + CON + GOA + PLA + MON + ENA) + (GSE + ITP); Model F (2-factor model): (ANT + SCA + CON + GOA + PLA + MON + ENA + GSE) + ITP; Model F (2-factor model): (ANT + SCA + CON + GOA + PLA + MON + ENA + ITP) + GSE; Model G (1-factor model): (ANT + SCA + CON + GOA + PLA + MON + ENA + ITP + GSE).

Table 4.2. *Descriptive Statistics, Reliability and Correlations (Pearson's r Coefficients) of Study Variables*

Variables	*M*	*SD*	Reliability (ω)	1	2	3	4	5	6	7	8	9	10	11
1. Anticipating Skill	3.44	0.71	.81	(.81)										
2. Scanning Skill	3.32	0.79	.74	.37**	(.74)									
3. Connecting Skill	3.33	0.85	.89	.36**	.42**	(.89)								
4. Goal Setting Skill	3.73	0.78	.86	.47**	.27**	.25**	(.86)							
5. Planning Skill	3.70	0.83	.87	.43**	.29**	.33**	.65**	(.87)						
6. Monitoring Skill	3.72	0.82	.90	.36**	.24**	.34**	.54**	.65**	(.90)					
7. Enacting Skill	4.16	0.74	.90	.32**	.22**	.29**	.44**	.43**	.45**	(.90)				
8. Situational Assessment Capacity	3.37	0.60	.84	.75**	.73**	.82**	.43**	.45**	.42**	.36**	(.85)			
9. Strategy Implementation Capacity	3.83	0.64	.93	.49**	.32**	.38**	.82**	.86**	.83**	.71**	.52**	(.93)		
10. General Self-efficacy	3.70	0.56	.87	.39**	.25**	.31**	.50**	.44**	.38**	.38**	.42**	.53**	(.87)	
11. Individual Task Proactivity	3.29	1.01	.88	.29**	.23**	.21**	.23**	.25**	.21**	.25**	.31**	.29**	.34**	(.88)

Note. n = 522; * p < .05; ** p < .01
M = mean; SD = standard deviation; Values in brackets are internal consistency reliability coefficients (Cronbach's alpha).

4.4.2. Structural Model

The relationship between the latent variables of our research model was tested by using Structural Equation Modeling (SEM). Based on the results, the hypothesized underlying model demonstrated satisfactory fit indices ($\chi^2(181) = 428.34$, $p < .05$; CFI = 0.93; TLI = 0.92; RMSEA = 0.06, SRMR = 0.06). As shown in Figure 4.1, all the factor loadings and path coefficients were statistically significant ($p < .01$), except for the strategy implementation capacity – individual task proactivity relationship. In general, the results obtained in the present study indicate that situational appraisal capacity was positively associated with general individual task proactivity ($\beta = .34$, $p < .01$), thus lending support for hypothesis 3. Nonetheless, there was no significant relationship between strategy implementation capacity and individual task proactivity. Hypothesis 4 is therefore not supported.

As recommended by Shrout and Bolger (2002), a bootstrapping technique was performed to test the mediation effect. Table 4.3 presents the direct and indirect effects of our theorized model and, as can be seen, results revealed that general self-efficacy partially mediate the relationship between situational appraisal capacity and individual task proactivity (direct effect $\beta = .34$, $p < .01$; indirect effect $\beta = .06$, $p <. 05$). Accordingly, hypothesis 5 examining the mediating role of self-efficacy in the situational appraisal capacity – individual task proactivity relationship is partially supported. Furthermore, a fully mediation role of the self-efficacy in the relationship between strategy implementation capacity and individual task proactivity was founded (direct effect $\beta = –.05$, $p = .66$; indirect effect $\beta = .08$, $p <. 05$). Thus, hypothesis 6 is supported.

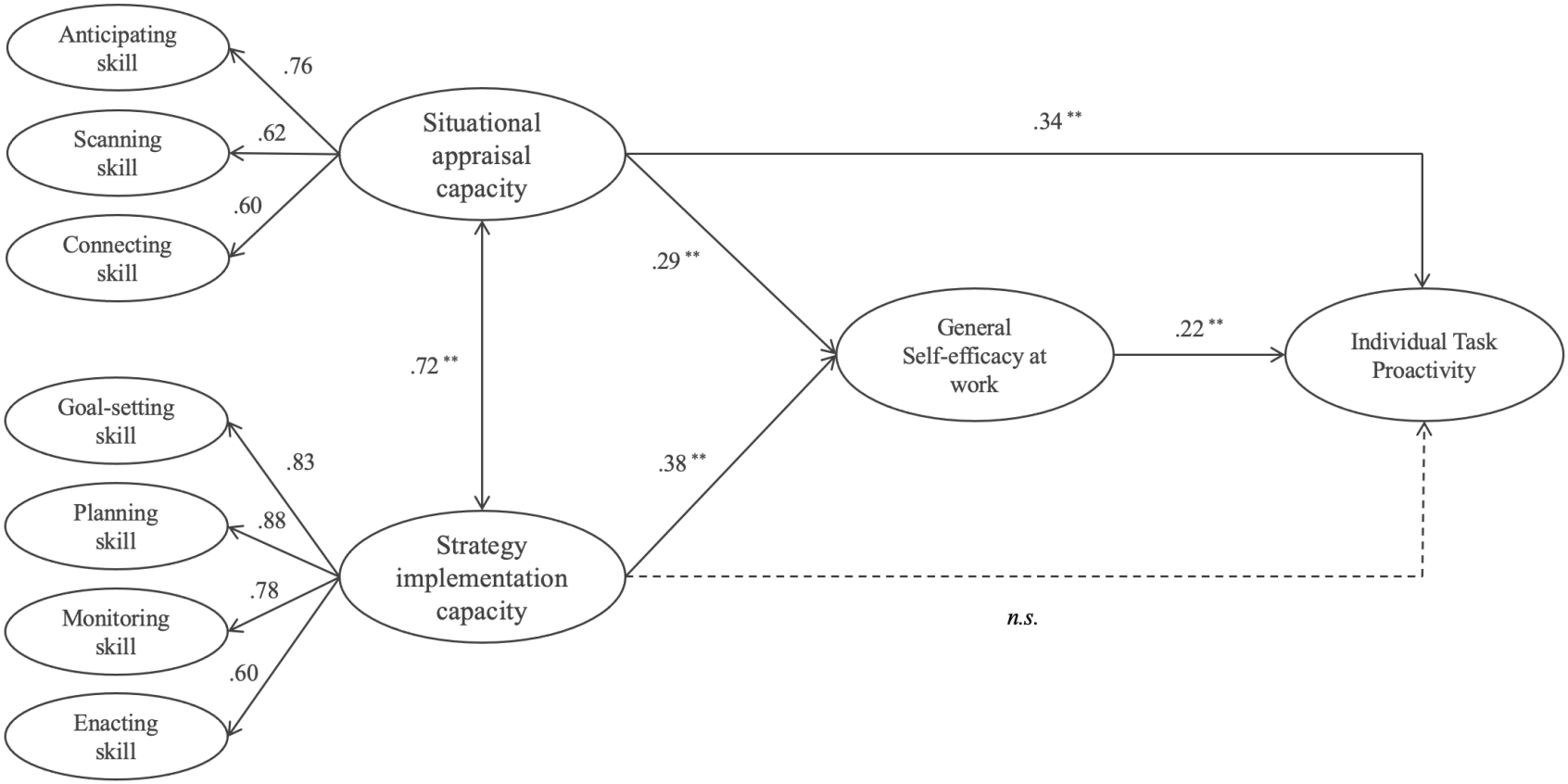


Figure 4.1. *Structural Model of Associations Between Strategic Capacities and Individual Task Proactivity through the General Self-efficacy at Work*

Note. $N = 522$; Coefficients presented are standardized path coefficients of the tested model.

** $p < .01$.

Table 4.3. *Mediation Analysis*

Effect	*β*	*SE*	95% CI		*p*
			LL	*UL*	
Direct effects					
SIT ➔ GSE	.29	.10	.10	.49	< .01
STR ➔ GSE	.38	.09	.18	.54	< .01
SIT ➔ ITP	.34	.12	.12	.59	< .01
STR ➔ ITP	–.05	.11	–.29	.15	.66
GSE ➔ ITP	.22	.06	.10	.36	< .01
Indirect effects					
SIT ➔ GSE ➔ ITP	.06	.03	.04	.25	< .05
STR ➔ GSE ➔ ITP	.08	.04	.05	.29	< .05

Note. N = 522; Bootstrapping sample = 10000; Standardized coefficients are reported. 95% CI: 95% confidence interval for *β*; *LL* = lower limit; = upper limit. SIT: situational appraisal capacity; STR: strategy implementation capacity; GSE: general self-efficacy; ITP: Individual task proactivity

4.5. Discussion

Drawing from the agentic SCT (Bandura, 1986, 2018), the main purpose of the present study was to examine how strategic skills in the form of two higher-order strategic capacities (i.e., situational appraisal, strategy implementation) relate to individual task proactivity at work through the mediating role of self-efficacy, which is considered a central psychological mechanism of the human agency. Overall, these results offer us various elements of discussion which in turn have research and practical implications vis-à-vis the human agency at work literature, and that are discussed below.

Regarding hypotheses 1 and 2, exploring higher-order strategic capacities, our findings suggest that the strategic skills (i.e., anticipating, scanning, connecting, goal setting, planning, monitoring, enacting) are indeed different and interrelated strategy-making capacities, but at the same time, two higher-order latent strategic factors named as situational assessment and strategy implementation capacities appear to shape the different strategic skills. These results

are especially relevant for a better understanding of not only the nature of these strategic skills but also the potential they have to develop the human agency for at least two reasons. First, the presence of higher-order strategic capacities shaping specific lower-order strategic skills are consistent with other studies on intelligence, which have shown how complex cognitive processes are explained by different stratum or forms of cognitive capacities (e.g., Coyle & Greiff, 2021; McGrew, 2009). For example, Silvia's (2008) work provided empirical evidence of the presence a higher-order variable like intelligence (g factor) shaping different lower-order variables or forms of intelligence such as fluid reasoning, verbal fluency, and strategy generation. Likewise, Silvia (2008) has found that while lower-order cognitive factors are modestly related to behaviors like creativity, a higher-order intelligence construct (including these lower-order cognitive factors) has the potential to better explain creativity. Second, with respect to the strategy-making process, these findings imply that the individual's strategy-making process capacity can also be explained through two higher-order capacities. In other words, while there is a supra-capacity (i.e., situational appraisal capacity) allowing people to make an overall assessment of their surroundings and potential changes, which shapes specific strategic capacities such as anticipating, scanning and connecting skills, there is also another supra-capacity (i.e., strategy implementation capacity) enabling people to establish and execute effective strategies which mold goal-setting, planning, monitoring and enacting skills. This opens up new research challenges to understand both deliberated- and implemental-oriented strategic capacities as well as how the different strategic skills work together or separately to face specific goals or in different phases of the motivated human action (Gollwitzer, 2018; Roe, 1999a).

Concerning hypotheses 3 and 4, examining whether higher-order strategic capacities are related to individual task proactivity, these findings highlight that the strategic supra-capacities appear to have different forms of relationship with proactive behaviors at work. On the one

hand, situational appraisal capacity was positively related to individual task proactivity, which implies that there is a direct relationship between the capacity to envision possible futures or to identify changes at work and proactivity at work. Considering that proactive behaviors refer to future-, change-, and self-starting oriented behaviors (Parker & Liao, 2016), it is therefore reasonable to expect that the capacity of gathering and providing information about potential changes in the context becomes essential to foster proactive behaviors. For instance, based on goal-regulation framework, prior studies have shown that envisioning future scenarios are related to other proactive behaviors such as innovative work behavior (Montani et al., 2015, 2017). On the other hand, strategy implementation capacity showed no apparent relationship with individual task proactivity. Contrary to our expectations, the capacity to design and implement strategic plans seems to be uncorrelated to proactive performance at work. A possible reason for this result is that the implemental side of the proactive behavior at work is not only related to personal (e.g., strategy implementation capacity) but also to organizational factors (e.g., perceived organizational support, organizational climate) (e.g., Marta et al., 2005; Montani et al., 2014). For instance, Parke et al., (2018) found that the daily planning (i.e., time management planning) was positively related to employee's daily performance, but such relationship was also moderated by the amount of the interruptions employees faced at work, thus showing that the planning skill (a representative example of the strategy implementation capacity) also depends on other organizational determinants.

With respect to hypotheses 5 and 6, evaluating the mediating role of self-efficacy in the higher-order capacities – individual task proactivity relationship, our results indicate that the psychological self-regulatory mechanism of the human agency, also known as self-efficacy, plays indeed a significant but different mediating role in determining how individuals transform their intentions into motivated action at work. That is, while self-efficacy showed a partial mediating effect on the situational appraisal capacity – individual task proactivity relationship,

a fully mediating effect was founded on the strategy implementation capacity – individual task proactivity relationship. Consequently, these findings raise at least three theoretical implications. First, the higher-order strategic capacities (i.e., situational appraisal, strategy implementation) are positively related to self-efficacy, thus providing preliminary empirical evidence of the potential these capacities have for developing human agency at work (Peña-Jimenez et al., 2021a). This is particularly important since it represents an empirical basis of how the two higher-order strategic capacities, as well as the lower-order strategic skills, work as a multi-capacity driver of the human agency at work (Hirst et al., 2020). Second, as expected, self-efficacy showed a positive relationship with proactive performance, as has been demonstrated by several meta-analytical studies on work-related performance (e.g., Carpini et al., 2017; Stajkovic & Luthans, 1998). Nevertheless, it is worth mentioning that in the current study we used the general form of self-efficacy at work, existing many other specific forms of self-efficacy (e.g., job-search self-efficacy, role-breadth self-efficacy) having the potential to better explain human action in other work-related contexts (e.g., Parker et al., 2010). Last, these findings support the idea that self-efficacy is a key regulatory mechanism linking strategic capacities and proactive performance at work (Bandura, 2006; Parker et al., 2010). Nonetheless, considering that the relationship between situational appraisal capacity and individual task proactivity was partially mediated by self-efficacy, these results also suggest that other psychological mechanism (e.g., affective, motivational) are involved in the complex process of becoming a competent employee. In fact, as has been pointed out by many agentic theories (e.g., Bandura, 2006; Parker et al., 2010), the general perception of self-efficacy represents an important psychological process regulating the human behavior; yet, being capable of doing something does not necessarily mean that a person will tackle in the same way all the organizational demands (Parker et al., 2010).

4.5.1. Research Implications

Overall, the current work makes some contributions to the human agency at work literature. First, these results lend preliminary empirical evidence on the role of two higher-order strategic capacities (composed of seven lower-order strategic skills) play in the development of human agency at work. Even though human agency has gained greater visibility because its potential to prepare the human workforce for a more uncertain and complex world of work (Bandura, 2018, 2019; Hirst et al., 2020, Yanchar, 2021), the strategy skills framework addressed in the present study is an emerging theoretical proposal which has as main purpose developing the strategy-making process capacity as a way to give individuals the possibility to actively control their actions and environment (Peña-Jimenez et al., 2021). Thus, rather than focusing on learning specific technologies that may rapidly change in the current technological revolution, we focus on the individual's capacity to develop and implement effective strategies to overcome current and future organizational challenges.

Second, this study has also allowed us to determine that these strategic capacities are related to a valuable form of work performance like individual task proactivity. This is a small but necessary step forward in addressing the challenge of unlocking the full potential of the human agency at work, especially in the digital age (Hirst et al., 2020). These results are also relevant for understanding how self-efficacy transforms these strategic capacities into proactive behaviors at work (i.e., proactivity). Nevertheless, future research is needed to determine, for example, how these strategic skills are related or transformed into effective (i.e., proficiency) and adaptive (i.e., adaptivity) behaviors at work, but most importantly, how other personal (e.g., learning and performance orientation) and organizational (e.g., leadership, management practices) correlates are involved in the motivated human action process (Gollwitzer, 2018; Roe, 1999a).

4.5.2. Practical Implications

This study also provides some practical contributions which are worth mentioning. First, our results suggest that promoting strategic capacities such as situational appraisal and strategy implementation, and more specifically anticipating, scanning, connecting, goal setting, planning, monitoring and enacting skills, could be beneficial for improving proactive performance at work, and consequently, a promising way forward the development of the human workforce in a time where people must face global, challenging and unexpected changes (e.g., covid-19 pandemic, technological revolution, new market trends) (Ackerman & Kanfer, 2020; Hirst et al., 2020). Put another way, organizations can introduce formal and informal HRM strategies to allow employees to learn or improve their strategy-making capacities as a way to actively manage and adapt their actions and work environment. For example, preparing individuals to acknowledge not only the formal capacity of a specific technological device but also to envision how this tool, along with other available technologies, can be used to meet existing goals or potential market demands, represent a way of developing situational appraisal capacity, and more specifically anticipating skill.

Second, considering that organizations are nowadays introducing new technologies that are transforming what and how people do their activities at work (Battistelli & Odoardi, 2018), strategic skills appear to be an essential personal asset for developing the sense of mastering or human agency at work. Our findings suggest that the two higher-order strategic capacities are positively associated with self-efficacy at work, which is a key regulatory mechanism of the human action that fosters proactive performance and many other forms of work performance (e.g., proficiency, adaptivity), but equally other positive psychological states (e.g., employee engagement, psychological well-being) (Albrecht & Marty, 2017). In other words, in times of serval changes in the world of work, organizations might be interested in developing not only

technical capacities but also those strategic capacities for exerting an active control over their environment by developing and implement effective and proactive strategies.

4.5.3. Limitations and Directions for Future Research

Although the present study offers important research and practical contributions, there are a number of limitations opening up new research avenues. First, the current work used a cross-sectional design to examine the relationship between the study variables. Even though this type of research design can be useful for providing preliminary evidence of theoretical proposals (Spector, 2019), further research using longitudinal design needs to be carried out to have a more comprehensive understanding of how these capacities are related, for instance, to the different phases of the motivated human action (Gollwitzer, 2018; Roe, 1999a). This is especially important for exploring causal and dynamic relationship between the higher-order strategic capacities (as well as the lower-order strategic skills) and other personal and organizational correlates.

Second, the present study used a self-assessment measure of strategic skills which provides an insightful view of how employees considered themselves to successfully perform their work-related activities. Nevertheless, the current technological development (e.g., big data, cloud computing, embedded systems) also offers us new opportunities to explore different indicators of human capacities at work (e.g., informal feedback, on-the-job observation, key performance indicators), thus providing potential research avenues to measure agentic skills but also to identify how these are related to important organizational outcomes. Moreover, emerging data analysis techniques (e.g., latent profile analysis, fuzzy set qualitative comparative analysis) can provide insightful and alternative explanations of the strategic skills in action, for example, by examining what are the most relevant skills for high-performance employees or how these strategic skills are mobilized jointly to cope with specific organizational requirements (including the use of different technologies).

Third, based on the human agency SCT (Bandura, 2006), we consider that strategic skills represents a fundamental set of personal resources, working like a master key opening the door of many other skills (e.g., cognitive, digital, functional business, interpersonal/managing people) but also to identify possible available organizational resources to meet a goal (Battistelli & Atzori, 2006; Peña-Jimenez et al., 2021). Though this work was focused on how strategic skills relate to proactive performance at work, future research can integrate different skill clusters to explore how they work conjointly to solve a problem at work.

4.5.4. Conclusion

The world of work and organizations as we know it today is fast becoming a more interconnected, challenging and changing environment (Murray et al., 2021), which needs people prepared to use more advanced and complex technologies, but equally individuals capable of actively managing and transforming their work environment by developing their human agency at work (Hirst et al., 2020). Drawing from the SCT (Bandura, 2018), the current study examined how two higher-strategic capacities (i.e., situational appraisal, strategy implementation), composing of seven lower-order strategic skills (i.e., anticipating, scanning, connecting, goal setting, planning, monitoring, enacting), were related (directly and indirectly) to proactive performance at work through the mediating role of self-efficacy, as a central regulatory mechanism of human agency. This study represents therefore a first attempt to evaluate how skills allowing individuals to make an appropriate situational assessment of their work environment, as well as to develop and implement effective strategies, become essential to boost the human agency at work, as a way to face the challenges of the Fourth Industrial Revolution (Hirst et al., 2020; Peña-Jimenez et al., 2021).

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Chapter 5

General Discussion

Chapter 5. General Discussion

The general aim of this thesis was to develop and assess a skill framework allowing people to foster their strategy-making capacities (from situational assessment to strategy implementation), as a form to deal with the work and organizational challenges of industry 4.0. Whereas considerable efforts have been made to identify skills required to solve immediate or emerging organizational demands (e.g., Dierdorff & Elligton, 2019; van Laar et al., 2018), skills fostering the human agency to deal with uncertain and complex contexts have been overlooked, and consequently, further research is needed to equip employees for evolving work environments and activities (Bandura, 2018; Hirst et al., 2020, Yanchar, 2021). In this regard, this thesis proposes to address the need to better understand different strategic skills having the potential to unlock the human agency at work, thus paving the way for an increasingly changing and challenging world of work and organizations. To do so, drawing from the human agency approach (Bandura, 2006, 2018), we carried out a theoretical review and different empirical studies addressing our specific research goals, and whose implications were presented and discussed in the previous chapters.

Based on the findings of all our studies, an integrated and general discussion of the theoretical, methodological and practical implications of this doctoral research are presented in this chapter. In addition, we present the strengths and limitations related to this work, thus lending further elements to allow readers having a critical overview of this thesis. Future research avenues are also offered to encourage organizational scholars, and more specifically work and organizational psychology researchers, to further study the nature, dynamic and correlates of strategic skills in different social, cultural and organizational settings. Last, we present the overall conclusion of this thesis.

5.1. Theoretical Implications

5.1.1. Skills for Industry 4.0: Much More than Technological Issues or Demands

The first implication of this thesis is that skills required in industry 4.0 goes beyond learning new technical skills or how to use new technological devices. For example, although digital technologies (e.g., Moodle, Blackboard Learn) have been widely used to offer remote learning programs by higher-education institutions before the COVID-19 pandemic, many such organizations had to ensure a fully remote e-learning experience during the lockdown, thus pushing the higher-education workforce to learn not only how to use these novel technologies (e.g., Zoom, Microsoft Teams) but also to design and implement strategies to adapt themselves and their new work environment (Turnbull et al., 2021). This is just one of many examples from different industrial sectors that illustrate the wide range of skills that are required in the digital age.

From a scholar perspective, the findings presented in chapter 1 allowed us to have a broad view of skills considered relevant in industry 4.0 and more specifically, a wide range of skills fostering decisional and strategy development of work processes. Our systematic literature review identified several specific skills (e.g., problem solving, communication, management, technical, digital literacy) that are currently suggested and explored by scholars. In addition, we provide a list of other reviews and several existing skill frameworks which were developed under other theoretical perspectives (e.g., Chaka, 2020; Kipper et al., 2021; van Laar et al., 2020), and beyond the nuances of the required skills, it was possible to identify not only technical skills but also strategic skills in all of them. By using the human agency approach, we also develop in the same chapter an integrated skill framework focused on functional capacities instead of isolated skills. The human agency skill framework distinguishes five skill clusters (i.e., cognitive, interpersonal/managing people skills, technological, functional business, strategic) that are grouped into three different functional capacities (e.g., core, enabling,

enhancing) to deal with organizational challenges of the digital age. This chapter provides thus a comprehensive skill framework highlighting that managing the digital age involves more than technical or basic cognitive skills.

From an empirical perspective, chapter 2 revealed that there is indeed a wide range of skills that are required to meet the challenges of Industry 4.0. In accordance with our human-centered approach, we explored skill considered relevant for employees working in a highly-technology company from aeronautic sector. We also had the unique opportunity to assess the skills required in two completely different social (i.e., before COVID-19 pandemic vs. during COVID-19 pandemic) and organizational (e.g., on-site work vs. telework) contexts through two cross-sectional studies in the same company. By using a wide range of skill descriptors, our results showed that there are several skills clusters (i.e., cognitive, interpersonal/managing people skills, functional business, strategic) that are essential to perform their job well by those employees that are already working with technologies such as additive manufacturing, advanced sensors and actuators, cloud systems and embedded systems in a company that is considered a representative case of industry 4.0. The results presented in chapter 2 also showed that skill requirements differ depending on the organizational role, that is, the skills required (e.g., cognitive, managing people, strategic, functional business) by organizational leaders (e.g., managers) were significantly different from those of subordinates (e.g., front-line staff), which is in the same line of previous research exploring skills focused on leaders (e.g., Guzmán et al., 2020; Mumford et al., 2007). Last, our findings suggest that just functional business skills were perceived as more valuable resources in an unexpected and uncertain context (i.e., during COVID-19 pandemic, telework), while cognitive, managing people and strategic skills remain statistically equivalent over time.

Overall, these results are consistent with proposals (e.g., Hirst et al., 2020; Montealegre & Cascio, 2020; Odoardi et al., 2021) stating that employees need to acquire new knowledge

and skills to embrace this technological revolution at work (e.g., cloud computing, collaborative robots, interconnected drones), but above all, to develop capacities to deal with uncertainty and develop creative solutions for using, transforming, and even destroying these technologies to adapt to a quickly changing world of work. Put another way, employees need not only different technical (e.g., technological) and basic (e.g., cognitive) skills, but also strategic skills to manage transformative contexts through effective strategies, having the potential to boost human agency at work.

5.1.2. Strategic Skills: Building the Workforce for a Changing and Challenging World of Work

The second implication of this work is that strategic skills represent a personal asset that allows people to deal with uncertain and complex contexts, through analyzing their environment, adopting objectives, developing and implementing action plans, and consequently, a resource worth developing to face the industry 4.0 challenges (Fridland, 2021; Peña-Jimenez et al., 2021). The strategic character of these skills means that solving a problem or meeting a goal involves more than an automatic response (or use of specific skills), it also requires a strategic control to decide when, where and how people must act, and which and why other (e.g., personal, contextual) resources are potentially needed to face an organizational demand (Fridland, 2021). Therefore, employees must anticipate future scenarios, scan their environment, establish goals, develop and implement actions plans to guide their actions to achieve their goals (Mumford et al., 2007; Battistelli & Atzori, 2006). Taking the above into account, we focused on developing the theoretical foundations of strategic skills and exploring the psychometric properties of a new measure to assess them.

Grounded on the agentic approach of the Social Cognitive Theory (SCT; Bandura, 1986, 2006, 2018), and more specifically action-regulation frameworks (Gollwitzer, 2018; Roe, 1999a), chapter 3 on the one hand defines which are the strategic skills and why these are

relevant from an ontological, psychological and organizational standpoints. In addition, in this section it is also developed the conceptual underpinnings of seven different but related skills (i.e., anticipating, scanning, connecting, goal setting, planning, monitoring, enacting) supporting the strategy-making process (from situational appraisal to strategy implementation) (Battistelli & Atzori, 2006; Gollwitzer, 2018; Roe, 1999a). As mentioned in previous chapters, we claim that strategic skills are essential skills, among other things, because their capacity to foster the self-regulation process at work (e.g., from goal setting to job-related action), support the strategy-making process (i.e., situation assessment, goal generation, decision-making, strategy implementation), and consequently, it is required appropriate measures to assess strategic skills. On the other hand, chapter 3 also presents the measurement development process of the Strategic Skill Questionnaire, a new measure designed to assess (within an organizational setting) the seven above-mentioned strategic skills, whose methodological implications will be subsequently discussed.

The theoretical postulates and results presented in chapter 3 open up new possibilities to understand the nature and the form of the strategic skills. Regarding their nature, we have investigated strategic skills in terms of capacities, while others propose to explore dispositional constructs (e.g., goal orientation, regulatory focus, proactivity, felt experience of failure) related to human agency by incorporating, for example, self-reflectiveness into research (Hirst et al., 2020). In this regard, this thesis sheds light on how some capacities, developed through different learning experiences, may become a valuable asset for solving problems at work, however, this also highlights the need for further research distinguishing strategic skills from other skill-related and agency-related constructs (Hirst et al., 2020; Yanchar, 2021).

As regards the form of strategic skills, on the one hand, this work has aimed at investigating the individual-level form of strategic skills, that is, how persons individually seek to exert control over themselves and their environment by using these strategy-making

capacities. Nevertheless, employees generally work with other people (collectively) to attain strategic goals in their organization, and hence, exploring how teams (e.g., project management team, business units) develop and mobilize strategic skills collectively (i.e., team-level, organization-level) deserves particular attention in future research. On the other hand, the form of strategic skills also refers to the importance of studying how these strategic skills act independently, or as a whole (e.g., in the form of higher-order capacities) to solve complex problems. For instance, Fridland (2021) argues that this strategic control may take the form of higher-order capacities shaping specific lower-order forms of skills, and therefore, these different complex forms capacities also need to be investigated.

To sum up, while previous studies (e.g., Mumford et al., 2007; Mumford et al., 2017) have addressed different strategic skills separately (or in terms of thinking skills), this thesis offers an integrated conceptual framework which allows us to further deepen our knowledge on the nature and form of strategic skills (from situational appraisal to strategy implementation) as a way to allow people to take control over their environment. This does not mean, of course, that strategic skills give individuals an absolute control over their environment, but designing, planning and implementing strategies can guide people to manage the continuous, complex, and rapid changes distinguishing industry 4.0 (Hirst et al., 2020; Fridland, 2021; Yanchar, 2018; 2021).

5.1.3. Strategic Skills: Fostering the Human Agency at Work

The third implication of this research is that higher-order strategic capacities (shaping lower-order strategic skills) are positively associated with proactive work performance (i.e., individual task proactivity), through the mediating role of a core psychological mechanism representing human agency (i.e., self-efficacy at work), thus lending preliminary evidence on the potential that strategic capacities have to develop not only human agency at work, but equally, other valuable organizational behaviors.

Drawing from SCT (Bandura, 1986, 2006, 2018), chapter 4 presents results from a cross-sectional study supporting evidence, on the one hand, that strategic skills (lower-order strategic constructs) may be shaped by complex forms of strategic capacities (higher-order strategic constructs). Our results suggest two-higher order strategic capacities (i.e., situational appraisal, strategy implementation), shape seven lower-order strategic skills (i.e., anticipating. scanning, connecting, goal setting, planning, monitoring, enacting), which is consistent with theoretical postulates (e.g., Fridland, 2021; McGrew, 2009) and empirical evidence (e.g., Silvia, 2008; Brady et al., 2020) claiming the presence of higher-order mental capacities (e.g., complex problem solving, work ability). These results therefore offer additional evidence on the form that strategic skills take, as well as different levels of strategic skills, which leaves open the question of whether there are different forms (or stratum) of strategic-related constructs: (1) strategic skills (Stratum I), (2) strategic capacities (Stratum II), and strategic competency (Stratum III).

On the other hand, chapter 4 examines the relationship between strategic capabilities (in higher-level forms) and proactive work performance, through the mediating mechanism of self-efficacy. More specifically, the results showed that the situational appraisal capacity – individual task proactivity relationship was partially mediate by self-efficacy, while the relationship between strategy implementation capacity and individual task proactivity was fully mediate by self-efficacy. These results are particularly relevant for two reasons. From a human agency viewpoint (Bandura, 1986, 2001), strategic capacities could be considered as a "control-oriented resource" (Yanchar, 2021), that can be used and developed to boost human agency at work, or stated another way, potential predictors of agency. This therefore poses the challenge of further evaluating the relationship that these strategic capacities, have to work alongside other skills (e.g., cognitive, functional business, managing people, technological), or even regulate them (as meta-skills) (Fridland, 2021), in order to foster human agency and other (e.g.,

cognitive, motivational) mechanisms (Hirst et al., 2020; Parker et al., 2010). From a proactivity standpoint, our findings revealed that strategic capacities are positively related to proactive work performance (Griffin et al., 2007), thus suggesting that these skills may also be related to many other proactive behaviors (e.g., voice, job crafting, role expansion) (Parker et al., 2010; Parker et al., 2019), but also to other forms of work performance (e.g., proficiency, adaptivity) (Griffin et al., 2007).

Summarizing, human agency, or the people's capacity to exert control over not only their own actions but also their environment (Bandura, 2006, 2018), has taken on greater importance in a time of new disruptive technological forces in the world of work (Ackerman & Kanfer, 2020; Hirst et al., 2020), and major social transformations (Heckhausen et al., 2019; Kooij et al., 2020). We consider that chapter 4 provides preliminary but insightful evidence about the potential that strategic skills have to develop human agency at work as well as many other organizational outcomes (Bandura, 2018, Hirst et al., 2020). Accordingly, although developing skills that are currently required by organizations (e.g., digital skills, technical skills) are useful and necessary to overcome immediate work challenges, fostering strategic skills also means putting humans (through control-oriented resources) at the center of the technological transformation of the world of work and organizations (Hirst et al., 2020).

5.2. Methodological Implications

5.2.1. Tracking the Skills Mismatch in Industry 4.0: A Comprehensive Measure

One methodological implication of the current work is related to the challenge of screening skills gap in industry 4.0. As presented in preceding chapters, to identify the skills required in a specific work context (e.g., job, business unit, organization, industrial sector, labor market) is a complex and challenging task because there are several different skills frameworks (Sanchez & Levine, 2012). This becomes even more complex because there are also several skills measures which differ substantially from each other regarding the way such instruments

assess skills (e.g., purpose, view of the job, organizational focus, time perspective, performance indicators, measurement approach) (Sanchez & Levine , 2009). From an organizational point of view, it is possible to distinguish two broad approaches for measuring which skills (as well as other personal attributes and resources) are required in a given organizational setting. The first is "job analysis", whose focus on describing job behaviors and past indicators of typical performance, and the second is "competency modeling" which seeks to identify what is required to influence organizational-oriented behaviors and high performance (for a review see Sanchez & Levine, 2009, 2012). Taking the latter approach as a reference, this thesis provides organizational scholars and practitioners with an adapted Italian version of a general screening measure for assessing the skills gap based on the *Occupational Information Network Content Model* (O*NET, Tippins & Hilton, 2010; Peterson et al., 2001).

Overall, as proposed in this work (see Chapter 2), this O*NET Content Model measure can be used in terms of skill clusters or functional capacities (e.g., cognitive, strategic, functional business, managing people), but also in the form of specific skill descriptors, as it was originally developed (Mumford et al., 2007; Tippins & Hilton, 2010; Peterson et al., 2001). Nevertheless, regarding more technical (or technological) skills, a measure will need to be developed for assessing skills related to the specific technological infrastructure of a given or expected work environment (e.g., Groselj et al., 2020; van Laar et al., 2019), human-technology synergy (e.g., Murray et al., 2021, Fréour et al., 2021), or even to take the advantage of technological environment (e.g., Bazine et al., 2020), which raises the need for the development of new measures that allow labor stakeholders evaluating technical skills, and more specifically technological skills, that are required in Industry 4.0.

5.2.2. Assessing Strategic Skills: Preliminary Psychometric Evidence

Assessing strategy-making process in terms of skills or functional capacities is the second methodological implication of this study. Based on SCT (Bandura, 2006, 2018) and

action-regulation models (Gollwitzer, 2018; Roe 1999a), the strategic skill framework which comprises seven different but related skills (i.e., anticipating, scanning, connecting, goal setting, planning, monitoring, enacting) was evaluated through a new measure (adapted to French language and cultural background). As presented in chapter 3, the Strategic Skills Questionnaire (SSQ), designed to be used in an organizational setting, showed satisfactory psychometric properties, thus becoming a useful instrument for uncovering the potential that strategic skills may have in uncertain and challenging times.

From a measurement development outlook, this doctoral research provides preliminary empirical evidence on the adequate psychometric characteristics of a multidimensional questionnaire assessing strategic skills, thus laying the foundation to check the adequacy of the nature and form of strategic capacities (Fridland, 2021). Nevertheless, as part of the iterative and ongoing process of improving the psychological measurement instruments, future research should expand the evidence on the validity of the results in other samples (e.g., university students), nature (e.g., dispositional vs. skills), form (e.g., stratum or different levels of strategic capacities), and alternative measurement approaches (e.g., situational judgment, supervisor-rated) (Fridland, 2021; Hirst et al., 2020; Zickar, 2020). Considering the above, there are still many challenges to assess strategic capabilities, but above all to understand how they act – together or separately – to face the work and organizational challenges in the digital age. Therefore, further developments on the SSQ or alternative forms to assess strategic capacities is essential not only for theoretical and measurement development but also to prepare the workforce of the future.

5.3. Practical Implications

5.3.1. Organizational Competitiveness Development: Promoting Upskilling and Reskilling

Upskilling and reskilling of employees as a way to promote organizational competitiveness is a first practical implication of this work. Currently, employees all over the world are already experiencing the changes of a more technological-driven world of work (e.g., new work environment, job resources, organizational demands), thus posing new challenges for different labor actors, and in particular for organizations. For instance, according to the Future of Jobs Report (World Economic Forum, 2020), about 55% of surveyed employers all over the world agrees that skills gap is one of the most important barriers to adopt new technologies in such companies. Therefore, among the different organizational challenges, skill development has become an essential strategy to contribute to the adaptation of the workforce to this new world of work (Ackerman & Kanfer, 2020; Scully-Russ & Torraco, 2020).

As previously presented (see chapter 2), our results raise the importance of developing training programs that consider the general needs of the entire company's workforce (e.g., technical requirements), but also the specific requirements associated to the organizational role (e.g., supervisors, managers) and the evolution of the company (e.g., social and organizational changes). For example, the results showed that the skills required by the organizational leaders (e.g., managers) were considerably higher than the skills required by the employees. Likewise, we identify that changes in the social and organizational environment (e.g., telework) modified the skills, as was the case with functional business skills. Accordingly, skill development training must be an ongoing process and must integrate essential elements of the specific organizational context (e.g., available resources, strategic priorities, internal organizational structure, market demands).

5.3.2. Training and Development: Building an Agentic Workforce

Preparing the workforce for mastering labor and organizational changes through strategy-making capacities is another practical implication of this study. As technological development advances, especially during the COVID-19 pandemic, most organizations are changing, with meaningful impacts on the skills required by the contemporary and upcoming workforce (Kniffin et al., 2021; Lund et al., 2021; Rudolph et al., 2021). For example, the explosive rise in teleworking in the last year has produced many changes in the world of work, and consequently, employees are learning to use not only new technological devices and applications but also new and different forms to manager an increasingly digital work environment (e.g., digital work platforms, virtual collaboration) to perform their work-related tasks effectively (Lund et al., 2021). In this regard, this study proposes to develop strategic skills to allow people to manage and transform their work environment through developing and implemental strategies.

As presented in chapters 3 and 4, strategic skills are personal resources allowing individuals to make an appropriate situational assessment and to develop effective strategies, thus becoming a key asset for organizations, higher education and vocational training institutions aiming for developing effective training for mastering a more and more digital, uncertain and complex world of work. As has been suggested (Cascio & Montealegre, 2016; Kanfer & Blivin, 2019), adopting new technologies in the workplace does not automatically transform into better work performance for organizations. While most skill taxonomies are focused on organizational requirements at a macro society level, we propose a skill framework which places people at the center of the technological transformation of organizations. For instance, the global survey of the World Economic Forum (2020) suggests that, for many employers, the list of most important skills (as independent resources) for 2025 will be as follows: (1) analytical thinking and innovation, (2) active learning and learning strategies, (3)

complex problem solving, (4) critical thinking and analysis, (5) creativity, originality and initiative, (6) leadership and social influence, (7) technology use, monitoring and control, (8) technology design and programming, (9) resilience, stress tolerance and flexibility, and (10) reasoning, problem-solving and ideation. By contrast, this study offers a theoretical skill framework (as functional and interconnected resources) which can be measured through the strategic skill questionnaire, thus allowing labor stakeholders to develop skill training programs with a special focus on the human agency (Peña-Jimenez et al., 2021).

5.4. Research Strengths, Limitations, and Future Research Avenues

We present below the research strengths and limitations allowing to better understand and appropriate analyze the current findings and as well as possible future research directions.

5.4.1. Strengths

This study has some strengths that are worth pointing out. First, the originality of the strategic skills as a functional and core multidimensional set of capacities within the human agency skill framework. While previous studies have contributed to identifying skills addressing specific organizational requirements (e.g., Chaka, 2020; Kipper et al., 2021; van Laar et al., 2020), we develop a comprehensive human agency skill framework, to then build and evaluate a theoretical model about the nature, form and value of strategic skills in the digital age (for a theoretical review regarding skill and strategic control, see Fridland, 2021; Yanchar, 2021). We therefore consider that strategic skills offer new possibilities for developing agency at work in the digital age (Hirst et al., 2020).

Second, the evaluation of skill requirements by employees working in a company with high technological development from the aeronautic and aerospace sectors. As part of the doctoral research, we had the opportunity not only to carry out a study on skill requirements in two different social and organizational contexts, but also to visit the facilities, learn about the technological developments and meet the technical and organizational specialists responsible

for monitoring and ensuring a successful and sustainable technological transformation in such industry 4.0 organization. This experience therefore became an invaluable input not only to understand organizational challenges but also the value of strategic skills in Industry 4.0 (Hirst et al., 2020; Kanfer & Blivin, 2019).

Third, the psychometric evidence on a measure to assess the skills gap and a new instrument to evaluate strategic skills. The present research offers an adapted Italian version of a measure that is widely used by organizational researchers and specialists (Dierdorff & Elligton, 2019), and the new Strategic Skill Questionnaire whose aim is to evaluate strategy-making capacities, based on action-regulation frameworks (Gollwitzer, 2018; Roe, 1999a) and the SCT (Bandura, 1986, 2018). Both instruments are a strength and an essential part of skills assessment in the digital age, thus laying the foundations to expand the forms of skills assessment (including strategic skills) in the increasingly digital work environment (Kanfer & Blivin, 2019; Wiggins et al., 2020).

Last, the expansion of the knowledge about skills fostering human agency through strategic control. Grounded on the conceptual foundations and empirical evidence of the agentic SCT (Bandura, 1986, 2006, 2018), this work examines the potential of a set of capacities (i.e., strategic skills) to promote not only human agency at work but also proactive behaviors, and more specifically, proactive work performance. In this regard, we address the challenge of better understand how humans can seize the opportunities of more uncertain, technological driven and complex world (e.g., for a theoretical review about agency research, see Bandura, 2018, Hirst et al., 2020).

5.4.2. Limitations

The present study also has some limitations that must be pointed out. First, cross-sectional design was used in some of our studies, which provides insightful information about how different variables relate to one another but do not explain complex and causal mechanisms

(Spector & Pindek, 2016). According to Spector (2019), though longitudinal studies shed light on casual relationships, cross-sectional designs are particularly useful for providing initial evidence of new theoretical developments, as in this work. Nevertheless, it would be useful to develop longitudinal design in future research to better understand explanatory mechanisms and dynamic processes (Zhou et al., 2019).

Second, the characteristics of the study participants and the sample size may represent a potential limitation. Although, we carried out a study whose aim was to explore skill requirements in a highly technological company, future studies could explore the requirements of workers from other industrial sectors and of different technological development in order to have a broader representation of the skills required in the context of Industry 4.0. Likewise, expanding the sample size in specific organizational settings will be important to establish the magnitude of the effect in a given research model, as has been proposed in recent methodological recommendations (Wang & Rhemtulla, 2021).

Third, self-report measures can also be considered as another limitation. Our doctoral research is based on the postulates of the SCT (Bandura, 1986, 2006, 2018), which focuses on capacities from the employee's point of view, nevertheless, there are other measurement approaches (e.g., situational judgment, supervisor-rated) that can provide alternative evidence on other behavioral indicators of strategic capabilities. Therefore, when possible, future studies should use multi-source data to explore this kind of measure or emerging research designs for investigating common method variance (Podsakoff et al., 2012; Williams & McGonagle, 2016).

A final limitation that must be taken into account is the measurement and integration of specific aspects of the organizational setting and technological environment. Although one of our studies was conducted in a company driven by cutting-edge technologies, other studies were carried out in a sample of employees of organizations from different industrial sectors and technology development. Taken together, these studies provide valuable information on skill

requirements in a highly technological organization but also traditional organizations, however, in order to better understand technology and human synergy, future research should explore how strategic skills act in certain organizational context (Johns, 2017, 2018), and build forms of conjoined agency (Fréour et al., 2021, Murray et al., 2021).

5.5. Conclusion

The current technological revolution (e.g., artificial intelligence, autonomous robots, big data, drones, virtual reality) is creating a more and more interconnected, digital, uncertain and complex world of work and organizations, also called Industry 4.0. In this context, skills research has become essential to address the current and future organizational challenges. Drawing from a human agency perspective, this research addresses the challenge of exploring, developing and evaluating a strategic skills framework, or a set of strategy-making capacities that allow individuals to manage and actively transform their environment. Altogether, our theoretical review and empirical studies provide not only a comprehensive view about skills related to industry 4.0, but also the theoretical underpinnings and preliminary evidence about the nature, the form and the organizational value of the strategic skills in the digital age. Thus, in an era of where new technologies seem to exert greater control over humans, research on skills having the potential of fostering human agency at work, and more specifically strategic skills, open up new opportunities for building an active and engaged workforce.

5.6. References

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Appendix

Additional Information

Appendix

Appendix 1. Chapter 1 - Studies Included in the Review

Author and Year	Skill Dimensions
Phi & Clausen (2020)	-Creative problem-solving, System thinking, Goal orientation, Teamwork, Networking
Onyilo, Arsat, Latif, & Akor (2020)	Basic Green Automobile competencies: -Information technology, Communication, Creativity and Innovative, Problem-solving and decision-making
Mitrović Veljković et al. (2020)	Emotional Competence -Self-regulation, Self-awareness, Attitudes toward changes
Babatunde (2020)	-Active learning and learning strategies, analytical thinking and innovation, attention to detail and trustworthiness, complex problem- solving, coordination and time management, creativity, originality and initiative, critical thinking and analysis, emotional intelligence, instruction, mentoring and teaching, leadership and social influence, management of financial, material resources, manual dexterity, endurance and precision, memory, verbal, auditory and spatial abilities, persuasion and negotiation, quality control and safety awareness, reading, writing, math and active listening, reasoning, problem-solving and ideation, reasoning, problem-solving and ideation, resilience, stress tolerance and flexibility, service orientation, system analysis and evaluation, technology design and programming, technology installation and maintenance, technology selection, monitoring and control, troubleshooting and user experience, visual, auditory and speech abilities.
Jafar et al. (2020)	A model focused on Technical and Vocational Education and Training teachers Technical: Subject matter expert, Instructional planning, Instructional delivery, Instructional evaluation, Technology application, Classroom management, Facilitate student, Motivate student, Student career development Non-technical: Analytical, Creativity, Critical thinking, Collaboration, Communication, Ethical, Innovative, Leadership, Lifelong learning, Professional development, Research, Social and cultural awareness

Author and Year	Skill Dimensions
Spöttl & Windelband (2020)	-Broad competences (as ‘new basics’), Context-specific competences, Abstract’ competences
Aprianti, & Sahid (2020)	A framework about the Economic Teacher's competency: -Pedagogical, Social, Personality, Professional
Dewi, Soekopitojo, Larasati, Kurniawan, & Hartanti (2020)	-Ethical understanding, Personal and social, Critical and creative, ICT literacy, Literacy, Numeracy
Lan (2020)	Generic competences for university graduates of the Tuning Asia - South East project (TASE): -Ability to work collaboratively and effectively in diverse contexts, Ability to use information and communication technology purposefully and responsibly, Ability to uphold professional, moral and ethical values, Ability to demonstrate responsibility and accountability towards the society and environment, Ability to communicate clearly and effectively, Ability to think critically, reflectively and innovatively, Ability to understand, value, and respect diversity and multiculturalism, Ability to carry out lifelong learning and continuous professional development, Demonstrate problem solving abilities, Ability to initiate, plan, organise, implement and evaluate course of actions GC11. Ability to conduct research, Ability to demonstrate leadership attributes, Ability to apply knowledge into practice.
Bischof-dos-Santos & de Oliveira (2020)	-Analytical expertise, Autonomy, Communication, Creativity, Multi-skilled and flexible, Problem-solving expertise, Project management, Relational capability, Technical expertise
Ramli, Rasul, & Affandi (2020)	Technology green skills competency in 4IR -Environmental knowledge (concepts), Environmental knowledge (applications), Environmental management, Environment awareness, Application of ICT, Innovation, System analysis, Problem solving, Element across curriculum

Author and Year	Skill Dimensions
Kruskopf et al. (2020)	A model focused on accounting and auditing field: Technical skills: Understanding software capabilities, Analysis skills, Data visualization, Knowledge of international standards, Knowledge of industry specific regulations, Basics of coding, Fintech, forensic tools, Data warehouse management, Enterprise resource planning experience Social skills: Strong communications, Conflict solving, Leadership, Risk management, Strategic decision-making, Emotional intelligence, ethical, Adaptability, Sales knowledge, Innovative/creative, Customer service orientation
Škrinjarić, & Domadenik (2020)	Key competences to Firm Performance: Generic competences: Motivation and organization, Project management and professionalism, Collectedness, conflict resolution and presentation, Advocacy, language fluency Specific Competences: Business communication, Basic algebra, Economics and business theory and practice, Advanced math and IT knowledge
Shufutinsky, Sibel, Beach, & Saraceno (2020)	-Agility, Communication, Adaptability, Collaboration, Social interaction, Time management, Strategic thinking, Resilience, Teamwork, Empathy, Critical thinking, Boundaries, Prioritization
Mohamad, Hanafi, Daud, & Toolib (2020)	-Hard skills, Soft skills
Pywowar-Sulej (2020)	A model focused on Human Resource Management Social: Communication and cooperation Methodological: Analytical competence, Complex problem solving, Decision making Personal: Willingness to learn Domain: Digital networks, Digital security, Coding competence, Process understanding, Interdisciplinary competence
Duong, Nguyen, & Nguyen (2020)	An analysis of skills shortage in Vietnam's Labor Market -Lifelong learning, Innovation, Adaptability, Problem solving, Foreign language, Organization

Author and Year	Skill Dimensions
Yoshino et al. (2020)	A three-cluster framework promoting a I4.0 professional through several skills: -Personal competencies, Social competences, Professional competences
Lim, Ab Jalil, Ma'rof, & Saad (2020)	Self-regulated learning: -Goal setting, Time management, Self-evaluation, Help seeking, Task strategies, Environmental structuring
Rampersad (2020)	-Problem solving, Critical thinking, Communication, Teamwork
Hernandez-de-Menendez, Morales-Menendez, Escobar, & McGovern (2020)	-Creativity, Entrepreneurial thinking, Problem-solving, Conflict solving, Decision making, Analytical, Research, Efficiency orientation
Juhro, Aulia, Hadiwaluyo, Aliandrina, & Lavika (2020)	A model based on Transformational leadership competencies: -Breakthrough, Agility, Emotional / Spiritual intelligence, Influencing other, Communication, Visionary, Problem solving, Decision making
Le, Doan, Nguyen, & Nguyen (2020)	-Lifelong learning, Creativity and innovation, Expertise and digitalization, Adaptability, Critical thinking and problem solving, Foreign language, Organizing and managing ability
Akyazi et al. (2020a)	A framework oriented to Machine Tool Sector -Technical Future skills, Future transversal skills, Future green skills
Rhee, Han, Lee, & Choi (2020)	-Analytical thinking, Autonomy, Creative attitude, Global-mindedness, Communication, Professional attitude, Leadership, Problem solving, Self-directed learning attitude, Teamwork, Interdisciplinary fluency, Interdisciplinary openness
Abd Majid, Hussin, & Norman, Kasavan (2020)	Employability

Author and Year	Skill Dimensions
Puriwat & Tripopsakul (2020)	Essential skills of Thailand 4.0 Innovation skills: Innovative thinking, Creative thinking, Critical thinking and problem solving Digital and information skills: Digital literacy, ICT literacy, Media literacy Life and career skills: Adaptability, flexibility and collaborative skills, Civic and global citizen, English
Jerman, Bertoncelj, Dominici, Pejic Bach, & Trnavceic (2020)	Competency framework focused on the automotive industry -Flexibility/adaptation to change, Technical literacy, ICT literacy, Innovation and creativity, Soft skills, Openness to learning
Lopez Rios, Lechuga Lopez, & Lechuga Lopez (2020)	-Leadership, Entrepreneurship, Innovation, Critical thinking, Problem-solving, Commitment to ethics and citizenship, Intellectual curiosity, Passion for self-learning, Collaborative work, Communication, Digital transformation
Akyazi et al. (2020b)	A skills taxonomy based on professional profiles in Civil Engineering grouped into the following clusters: -Generic and Essential
Fareri, Fantoni, Chiarello, Coli, & Binda (2020)	Just a few examples of skills listed in the proposal Everyday execution skills: Business acumen, Ccopex, Change management, Computer literacy Operational skills: Continuous improvement, Cost leadership, Customer quality, Innovation Functional skills: Cost techniques, Direct labor efficiency, EEH&S management, Equipment
van den Berg, Stander, & van der Vaart (2020)	Different skills related to core themes: -Contextualizing HR data and information, Continuous learning, Stakeholder relationship management, Cultivating positive organizational practice

Author and Year	Skill Dimensions
Oksana, Galstyan-Sargsyan, Lopez-Jimenez, & Perez-Sanchez (2020)	Transversal competences: -Comprehension and integration, Application and practical thinking, Analysis and problem solving, Innovation, creativity and entrepreneurship -Design and projects, Teamwork and leadership, Ethical, environmental and professional responsibility, Effective communication, Critical thinking, Contemporary problems knowledge, Lifelong learning, Planning and time management, Specific instrument competence Language/linguistic competences -Listening, Speaking, Reading, Writing, Mediation, Pluricultural and plurilingual competence, Online training competence
Mingaleva & Vukovic (2020)	-Judges importance (Q1), Analyses tasks (Q2), Identifies factors (Q3), Learns from mistakes (Q4), Seeks simplest solutions (Q5), -Makes effective decisions (Q6), Thinks intuitively (Q7), Thinks 'outside the box (Q8), Is able to learn (Q9), Thinks quickly (Q10)
Pauceanu, Rabie, & Moustafa (2020)	Employability skills: -Complex problem solving, Critical thinking, Creativity, People management, Coordinaiton with others, Emotional intelligence, Decision making, Service orientation, Negotiation, Cognitive flexibility, Future foresight
Flores, Xu, & Lu (2020)	Soft workforce: Flexible and social Hard workforce: Professional and dexterous Cognitive workforce: Intelligent and analytical Emotional intelligence workforce: Self-aware and empathetic Digital workforce: Digital literacy and digital interactive

Author and Year	Skill Dimensions
Iñiguez-Berrozpe, Marcaletti, Elboj-Saso, & Garavaglia (2020)	Computational-Critical thinking
Akor et al. (2019)	Employability skills: -Creativity and innovation, Critical thinking and problem solving, Communication, Collaboration, Information literacy -Technology usage, Career/life skills, Personal/social responsibility
Azmi, Kamin, Md Nasir, & Noordin (2019)	-Technical, Non-technical
Mazurchenko & Maršíková (2019)	Digital skills to HR managers: -User a word processor, Create a spreadsheet, Use of internet, Email, Social media, video calls, Use software, Programming, Design and maintain ICT, Programme and use, Programme and use robots
Egcas (2019)	-Critical thinking, Complex problem solving, Creativity, People management, Cognitive flexibility, Coordinating with others, Judgment and decision-making, Emotional intelligence, Service orientation, Negotiation, Adaptability
Indrawan & Lay (2019)	-Pedagogical, Professional, Social, Personality, Critical, Creative, Communicative, Collaborative
Kamaruzamani, Hamid, Mutalib, & Rasul (2019)	Emotional intelligence attributes -Understanding one's emotions, Self-emotional awareness, Conscientiousness of emotions, Emotional influence, Managing emotions
da Silva, Luiz Kovaleski, & Negri Pagani (2019)	Different skills related to different profiles (based on a Systematic Literature review)
Kuzior & Sobotka (2019)	Metacompetence catalogue for the business service sector: -Information and communication, Psychosocial, Ecological and sozological, Economic, Ethical, Intercultural, Gender

Author and Year	Skill Dimensions
Popkova & Zmiyak (2019)	-Social, and Technical
Venter, Herbst, & Iwu (2019)	-Functional future, Essential future, Emerging future
Liboni, Cezarino, Jabbour,	Skills mainly oriented to Supply Chain Management
Oliveira, & Stefanelli (2019)	-Technical, Personal, Social
Teng, Ma, Pahlevansharif, &	Employability skills:
Turner (2019)	-Self-management, Communication, Team-working, Interpersonal, Working under pressure, Imagination, Critical thinking, Willingness to learn, Attention to details, Planning, Responsibility, Insight, Professionalism, Maturity, Emotional intelligence
Lee, Park, & Lee (2019)	-Entrepreneurial, Technical, Marketability
Siddoo, Sawattawee, Janchai, & Thinnukool (2019)	-Professional skills and IT knowledge, IT management and support, IT Technical
Ally (2019)	A framework oriented to become digital teacher -General, Use digital technology, Develop digital learning resource, Re-mix digital learning resources, Communication, Facilitate learning, Pedagogical strategies, Assess learning, Personal characteristics
Whysall, Owtram, & Brittain (2019)	-Commerciality, Client management skills, Relationship and communication skills, Collaboration, Systems thinking, Market focus, Leadership capability
Maisiri, Darwish, & van Dyk (2019)	Technical skills: -Technological skills, Programming skills, Digital skills Non-technical skills/soft skills -Thinking skills, Social skills, Personal skills
Ra, Shrestha, Khatiwada, Yoon, & Kwon (2019)	Learnability -Cognitive skills, Soft skills

Author and Year	Skill Dimensions
Longo, Nicoletti, & Padovano (2019)	-Cognitive capabilities, Psychological attitudes, Physical skills
Azmi, Kamin, Noordin, & Md. Nasir (2018)	Non-technical skills: -Communication skills, Teamwork skills, Critical thinking and problem-solving skills, Entrepreneur skills and computer skills
Łupicka & Grzybowska (2018)	Three clusters of competencies: -Technical, Managerial, Social
Kazancoglu & Ozkan-Ozen (2018)	-Combining know-how related to a specific job or process (C1); Flexibility to adapt new roles and work environments (C2); Continual Interdisciplinary learning and cooperation (C3); Knowledge on IT and production technologies (C4); Organizational and processual understanding (C5); Ability to interact with modern interfaces (C6); Trust in new technologies (C7); Awareness of IT security and data protection (C8); Ability of fault and error recovery (C9); Ability of dealing with complexity and problem solving (C10); and Thinking in overlapping process (C11)
Jerman, Bach, & Bertoncelj (2018)	Four clusters of skills based on a bibliometric analysis -Technical, Methodological, Social, Personal
De Andrade Régio, Gaspar, do Carmo Farinha, & De Passos Morgado (2017)	English language skills
Carter (2017)	-Communication/people, Collaboration, Flexibility, Critical thinking, Data analysis, Creativity/innovation, Marketing, Leadership, Project management, Horizon scanning/future planning, Advocacy/politics
Eberhard et al. (2017)	-Social, Cognitive, Personal/mental abilities, Process, System, Technical, Content, Intercultural, and Resource management

Author and Year	Skill Dimensions
Régio, Gaspar, Farinha, & Morgado (2016)	-Workforce language skills, Intercultural communication abilities
Kannan & Garad (2020)	-Technical, Methodological, Social, Personal
Cimini, Boffelli, Lagorio, Kalchschmidt, & Pinto (2020)	-Technical, Methodological, Personal, Interpersonal
Kruger & Steyn (2020)	-Innovation, Creativity, Integrate business and technology, Leadership and communication, Networking and sales
Low, Gao, & Ng (2019)	Soft skills: -resilience, curiosity, adaptability, entrepreneurial thinking, pursuing convictions, vision, Emotional sensing, Insight, Empathy
Adepoju & Aigbavboa (2020)	-Communication, Teamwork/coordination, Problem solving, Critical thinking, Decision making, Technological/digital competence, Programming/coding, Cyber security, Data analytics, Human machine interaction
Blayone & Van Oostveen (2020)	A five-dimensional worker readiness model -Technological, Flexibility, Inter-agent, Interpersonal, Innovation

Appendix 2. Chapter 1 - References Included in the Review

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