FUTURE SKILL TRENDS: HOW IS JOB AUTOMATION CHANGING THE SKILL REQUIREMENTS OF JOBS?

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Abstract

A major part of the current discourse about the future of work centers around the idea that, within the context of advanced economies, newly emerging, sophisticated automation technologies that have the potential to perform a wide range of work tasks currently carried out by human workers, and typically include, among others, artificial intelligence, smart robotics, and machine learning, will be rendering a significant number of workers redundant, thereby causing widespread technological unemployment. However, this alarmist vision concerning the future of work, in which it is imagined that automation will make a large number of workers obsolete, has lately been refuted by recent studies. However, although it is highly unlikely that automation will effectuate the widescale destruction of jobs, it is nevertheless expected that the increasing adoption and implementation of modern automation technologies into the work environment will change the nature of work in fundamental ways. In view of this, while certain job roles are expected to be eliminated as well as newly created as a result of automation, it is anticipated that the majority of job roles will be substantially reshaped and redefined due to automation. Based on this, it is expected that the demand for skills that are required to adequately perform a given job role will also undergo certain changes. Due to the importance for various societal stakeholders including workers, businesses, as well as education providers to obtain and develop an understanding about future skill trends that will ultimately shape the skill requirements of jobs, the present thesis aimed to obtain relevant and valuable insights in terms of how automation is changing the skill requirements of jobs within the context of advanced economies, thereby seeking to contribute to existing knowledge in this research field. In view of this, in order to generate a coherent answer to the above-mentioned research question asked, both an extensive review of the literature as well as a qualitative research study in the form of expert interviews were conducted. While the findings obtained by means of the literature review yielded valuable insights regarding the central research topic, the insights derived by means of the expert interviews generated a number of additional insights of high value that enriched the key literature findings. Overall, the synthesized findings from both the literature review together with the expert interviews showed that the increasing adoption and implementation of modern and sophisticated automation technologies into the work environment are expected to shape future skill trends that are considered to ultimately change the skill requirements of jobs. More specifically, the findings demonstrate that, in general, skills pertaining to the categories of advanced cognitive skills, social and emotional skills, technological and digital skills, as well as systems skills will likely increase in demand within the near future, thereby changing the skill requirements of jobs accordingly. In addition, according to the overall findings of the present work, skills pertaining to the categories of physical and manual skills as well as basic cognitive skills are anticipated to decline in demand due to automation, which, as a consequence, is expected to, again, shape the skill requirements of jobs accordingly. Further, while obvious trends in terms of future skill demand could be identified with regard to each distinct skill category mentioned above, the findings also highlight that, as a result of increasingly automated work environments that are also considered to increase in complexity as a result of automation, future skill trends and their associated changes in the skill requirements of jobs will also likely reflect the relevance for workers to obtain and develop a diverse skill portfolio encompassing various skills pertaining to the distinct skill categories that are anticipated to increase in demand within the context of automation. All in all, while this work entails certain limitations that need to be acknowledged, the findings generally yielded rich, timely, and valuable insights that indicate that the increasing adoption and implementation of modern automation technologies into the work environment will effectuate changes in the skill requirements of jobs that, in turn, entail important implications for various societal stakeholders that are also addressed within the context of this thesis. Lastly, it is important to stress that several areas for future research that were highlighted by the present work may complement and enrich the conclusions drawn in the realm of this thesis.

Keywords: future of work, automation technologies, artificial intelligence, skills, future skill trends, skill requirements

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1 Introduction

1.1 Background

During the past ten years, an array of pioneering and innovative technologies emerged that indicated and reflected the beginning of the so-called fourth industrial revolution (World Economic Forum (WEF), 2020). Within the era of this fourth industrial revolution that is driven by ongoing technological progress, innovation, and the confluence of emerging disruptive technologies, the economy as well as the nature and world of work in general are expected to undergo substantial changes (Seet et al., 2018; Universities UK, 2018), with sophisticated automation technologies that have the potential to execute a wide range of work tasks currently carried out by human workers being at the core of these changes (FutureLearn, 2020; McKay et al., 2019). As argued by Baweja et al. (2016), within the context of the fourth industrial revolution, ongoing technological progress and change are enabling "ever greater levels of automation" (Baweja et al., 2016, p. 3). In view of this, the convergence of a variety of technologies that entail a strong disruptive power including artificial intelligence and robotics and that are driving this era of the fourth industrial revolution is expected to cause significant changes across nearly every industry in the world (Baweja et al., 2016; D2L Corporation, 2018; FutureLearn, 2020). In light of this and according to Universities UK (2018), the fourth industrial revolution is viewed as being different to prior industrial revolutions due to both the pace of change that is expected to occur as well as the degree of disruption it is anticipated to effectuate. In relation to this, Engler et al. (2018) argued that technology was the main driver of job disruption within the past few decades and that the pace of change is expected to increase. With regard to this, Engler et al. (2018) remarked that fast-paced technological change including recent advances in modern automation technologies, such as artificial intelligence, that have the capabilities to carry out an increasing range of work tasks, will substantially affect a wide range of jobs typically performed by human workers. Further, as remarked by the WEF (2020), businesses are redirecting their strategic orientation in order to leverage the benefits and opportunities provided by modern and sophisticated automation technologies that, as remarked by Lamb et al. (2018), are generally designed to carry out tasks hitherto performed by human workers. With regard to this, the WEF (2020) found that, by 2025, the utilization of the capabilities of modern automation technology will be more widespread compared to past years, and that the work hours carried out by automation applications will equal the working hours spent by human workers (WEF, 2020). Further, the WEF (2020) found that, due to the changes brought about by the ongoing global COVID-19 pandemic, businesses are planning to increase the pace of their job automation strategies. More specifically, the findings obtained by the WEF (2020) suggest that around 80 percent of business leaders are speeding up the automation of their work processes (WEF, 2020).

In view of the aforementioned points, AlphaBeta (2017) pointed out that "technological change has long been a source of anxiety for workers" (AlphaBeta, 2017, p. 6), while Muro et al. (2019) noted that the power of automation is often associated with fears that technological advances in terms of modern automation technologies will be accompanied by a widespread destruction of jobs. However, history implies that past fears for automation to effectuate widescale unemployment have been unfounded as, in essence, prior waves of automation have resulted in enhanced prosperity, together with increased productivity and employment without generating widespread unemployment (AlphaBeta, 2017). In view of this, Oschinski and Wyonch (2017) stressed that "technological change has been the hallmark of economic progress throughout human history" (Oschinski & Wyonch, 2017, p. 2). In light of this statement, Oschinski & Wyonch (2017) noted that the conventional perspective about technological change, based on past events and experiences of prior time periods of industrial change, is that both technological advancements along with innovations are aspired and aimed for due to their potential positive effects on productivity that, in turn, may positively contribute to greater incomes by means of economic growth (Miller & Atkinson, 2013; Oschinski & Wyonch, 2017). As emphasized by Oschinski & Wyonch (2017), throughout the past, technological change was generally associated with many beneficial outcomes including decreased poverty as well as increased standards of living and overall well-being. In relation to the arguments provided by Oschinski & Wyonch (2017), AlphaBeta (2017) argued that, in today's age, automation may present an opportunity to leverage and exploit the power of modern automation technologies and machines to ameliorate human lives by raising prosperity along with increasing wages, living standards, and work conditions (AlphaBeta, 2017).

Nevertheless, while times of vast technological change can generate many beneficial outcomes as outlined above, it also has the power to cause great turmoil (Bughin et al., 2019; Ernst et al., 2018; Fernández-Macías, 2018; Raj & Seamans, 2019). In view of this, recent advances in automation, which broadly refers to “the replacement of human beings with machines, robotics or computer systems to carry out an activity” (Frontier Economics, 2018, p. 13), are, once again, causing fears and concerns among a number of economists, who worry about mass job destruction due to increasing technological progress (Oschinski & Wyonch, 2017). Thus, while innovation and technological progress are key drivers of productivity growth and constitute a basis for enhanced standards of living, recent advances in the fields of computing and robotics enable businesses to increasingly displace human labor with machines (Engler et al., 2018). In view of this, Manyika, Lund, Chui et al. (2017) stressed that, while job automation does not present a new phenomenon and fears about its impact on employment have been voiced in the past, the rapid recent progress and development regarding modern automation technologies as cited above, such as artificial intelligence and robotics, have, once again, incited new fears about automation’s effect on the number of jobs (Manyika, Lund, Chui, et al., 2017).

Self-driving cars, machines that have the ability to read X-rays, and algorithms that provide answers to customer service inquiries all constitute manifestations of sophisticated and novel forms of automation (Manyika, Lund, Chui, et al., 2017). Further, recent progress in artificial intelligence enables machines to outperform human workers in the domain of perception as demonstrated through driverless cars and in the area of pattern recognition and calculation that may be applied to assist in providing medical diagnoses (Engler et al., 2018). As these examples of technological advances provided above illustrate, we seem to enter a new age of automation, in which sophisticated automation technologies including artificial intelligence and machine learning do not only have the capacity to perform activities and tasks that, so far, could solely executed by human workers, but are increasingly capable to even surpass the human level of performance (Manyika, Lund, Chui, et al., 2017). As noted by McKay et al. (2019), increasingly advanced automation technologies may result in a more fast-paced, intensive, wide-scale, and, ultimately, more disruptive automation (McKay et al., 2019). In this sense, the rapid progress in sophisticated automation technologies, such as artificial intelligence and robotics, raises profound concerns if there will be sufficient work in the future to secure full employment (Hoffman et al., 2020; Manyika, Lund, Chui, et al., 2017). In view of the aforementioned points, the inevitable question arises of how continuous progress and advances in automation technology will affect jobs and, in essence, work in general (see e. g. Ernst et al., 2018; Fernández-Macías, 2018; Raj & Seamans, 2019; Payton & Knight, 2018).

In view of this, recent media and prevalent business press regularly put forward narratives that mirror and potentially incite prevailing fears about automation displacing a large number of workers (see e. g. Dahlin, 2019; West, 2018). In this regard, the current debate centering around the topic of automation and the future of work reflects the widespread attention this topic has, again, gained in the last few years (Hoffman et al., 2020). Corporations including Accenture, Deloitte, and McKinsey, popular media, such as Harvard Business Review and the National Centre for Vocational Education Research (NCVER), as well as academia (see e. g. Autor, 2015; Frey & Osborne, 2013; Manyika et al., 2017) are counted among the many voices contributing to this debate (Hoffman et al., 2020). In light of this, while some voices take a more optimistic stance regarding the future of work within the context of automation (see e. g. Arntz et al., 2016; Autor, 2015), other voices including Frey and Osborne (2013) along with provocative media headlines, such as "Robots could take over 20 million jobs by 2030" (Taylor, 2019) and "Robots on the rise as Americans experience record job losses amid pandemic" (Aratani, 2020), reflect a more anxious or pessimistic stance when addressing the future of work and employment within the context of ongoing technological progress in terms of automation, thereby potentially inciting rising fears about widespread unemployment potentially brought about by ongoing technological progress in the context of automation (Dahlin, 2019).

1.2 Problem Statement & Research Question

As mentioned above, the pervasiveness and advancing capacities of modern automation technologies are once again causing fears in terms of how automation will affect employment levels in advanced economies within the near future (Hoffman et al., 2020; Manyika, Lund, Chui, et al., 2017). Due to the prevalence and importance of the topic of the future of work in the context of increasingly automated work environments along with the interest this subject has attracted during the last few years, a substantial number of research studies and other academic literature have been published in recent years with the aim to increase the general understanding and to provide valuable insights in terms of how job automation is likely to impact the future world of work within the coming years (see e. g. Arntz et al., 2016; Manyika et al., 2017; Nedelkoska & Quintini, 2018). While some scholars and researchers are envisioning a rather alarmist future scenario with regard to the future of work within the context of automation (see e. g. Frey & Osborne, 2013) by stressing the so-called substitution effect of automation, which generally refers to the situation in which human workers are replaced by automation and thus, in which the adoption and implementation of modern automation technologies work as a substitute for human workers (Frontier Economics, 2018), and with it the potentially adverse consequences of the increasing adoption and implementation of sophisticated automation technologies including widespread job losses caused by automation and its wide-scale substitution effect, others are challenging these rather pessimist predictions by emphasizing the complementary effect between human workers and automation technologies along with the potential benefits and opportunities of automation for economies and societies (Bughin et al., 2019; Gentili et al., 2020). Overall, while there is a lack of agreement regarding the extent of the so-called substitution effect of automation (see e. g. Arntz et al., 2016; Frey & Osborne, 2013; Nedelkoska & Quintini, 2018), the more recent voices addressing the future of work in the context of automation generally suggest that widespread unemployment brought about by automation is unlikely to happen within the near future (Arntz et al., 2016; Manyika et al., 2017; Oschinski & Wyonch, 2017). However, even though ongoing technological change within the context of automation seems unlikely to effectuate the widescale destruction of jobs as stressed by various scholars and researchers, the nature of work and jobs along with the work tasks that human workers are required to carry out are anticipated to undergo substantial changes within a wide range of occupations due to increasingly automated work environments, thereby also changing the skill requirements of the respective jobs (Patscha et al., 2017; Seet et al., 2018). As stressed by Seet et al. (2018), the increasing adoption and implementation of modern automation technologies into the work environment will have profound effects on the demand for skills.

In view of the aforementioned points, it is, according to Hajkowicz et al. (2016), essential to gain insights and improve understanding of the impact and effects of this new wave of automation powered by sophisticated technologies on the nature of work and jobs along with the corresponding shifts or changes in the skills that are required to succeed in increasingly automated workplaces in order to design and take appropriate action measures to prepare for and manage the anticipated changes, thereby ensuring that future economies may fully seize the potential and opportunities provided by automation while simultaneously preparing and assisting workers to thrive in this changing world of work. Consistent with the above-mentioned points, the World Economic Forum (WEF, 2016) stressed that, within the context of a dynamic work landscape increasingly influenced by ongoing technological change, it is of utmost importance to provide forecasts in terms of future skill requirements of jobs in order for a variety of societal stakeholders including individuals, businesses, and governments to leverage the opportunities offered by this technological revolution while simultaneously ensuring that unwelcome effects are alleviated (WEF, 2016). Thus, in light of the arguments provided above, it will be essential, as emphasized by Manyika, Lund, Chui et al. (2017), to determine the skills that will be increasingly required in order to succeed in the future world of work. In view of the aforementioned points, the present thesis seeks to explore how job automation is changing the skill requirements of jobs across advanced economies. Based on this, the present work aims to answer the following research question:

How is job automation changing the skill requirements of jobs within the context of advanced economies?

1.3 Systematic Literature Review & Qualitative Research Approach

As a means to yield relevant information and insights about the central focus topic of this thesis, the present work will include a systematic literature review synthesizing relevant and dominant literature related to the research field of job automation and its potential impact and influence on the nature of work, employment, jobs and associated skill requirements. This literature synthesis that encompasses a variety of recent, international studies, articles, and reports addressing the topic of job automation and its implications for the future world of work seeks to yield a comprehensive picture and overall understanding about how modern and sophisticated automation technologies, such as artificial intelligence and robotics, are affecting and shaping the world of work and jobs in particular, and, based on the resulting changes and dynamics due to job automation, aims to identify how the demand for skills is changing within the near future and how, ultimately, the skill requirements of jobs are expected to change. In view of this, obtaining a comprehensive understanding in terms of the dynamics underlying the anticipated future skill shifts is important in order to provide a thorough and coherent answer to the above-cited research question. Thus, in order to explore and identify not only the anticipated future skill trends within the context of increasingly automated work environments, but also to understand the dynamics underlying these expected trends in terms of the skill requirements, an extensive review of existing forward-looking literature relating to the topics of how the adoption and implementation of modern automation technologies including artificial intelligence and robotics into workplaces across advanced economies are expected to impact jobs and work in general, and how these effects of automation are, in turn, anticipated to change and shift the general skill requirements of jobs was therefore carried out. For the sake of identifying relevant literature, the literature search was conducted based on suitable and adequate keywords relating to the aforementioned topics. These keywords encompassed, but were not limited to, *future of work, automation, modern automation technologies, effects of job automation, skills of the future, and skill requirements*. Further, for the purpose of the literature review conducted in the realm of this thesis, only literature sources that have its focus on advanced economies, which typically refer to the highest developed countries in the world and are commonly described as entailing high levels of gross domestic product per capita along with having a strong level of industrialization (Liberto, 2019), were chosen and reviewed for this literature analysis. One reason for this chosen focus constitutes the fact that the effects of automation throughout the next few years are anticipated to be much stronger in advanced economies as opposed to developing economies (Gumbel, 2018). In view of this, as found, for example, by the OECD (2019b), industrial robots are, to a much greater extent, utilized in advanced economies, which implies that the topic of automation is especially relevant for countries belonging to the category of advanced economies (OECD, 2019b).

Further, the theoretical findings derived from this in-depth literature review will serve as a knowledge and discussion base for the subsequent qualitative research study conducted in the realm of this thesis. Thus, in order to answer the above-raised research question, the present thesis does not only make use of a comprehensive and in-depth literature review encompassing a variety of recent foresight studies within the domain of job automation and its implications for the future world of work, but further seeks to enrich the already available information about the influence of job automation on work and jobs in general, and skills and competencies in particular by means of expert interviews with selected individuals that possess relevant knowledge about these themes presented above.

In light of this, it is important to emphasize that the present thesis along with its findings from both relevant literature as well as the qualitative research study conducted in the realm of this thesis do not provide any specific forecasts with regard to sector-specific anticipated future skill trends and changes within the context of increasingly automated work environments across advanced economies. Rather, by performing an extensive literature review together with a qualitative research study in the form of expert interviews, the present work will highlight general skill trends and changes that are anticipated to unfold within the context of increasingly automated work environments within the coming years.

1.4 Relevance and Potential Contribution

By gathering and analyzing various foresight studies along with collecting valuable future-oriented expert opinions, viewpoints, and insights to answer the central research question of this work, the present thesis can be characterized as a foresight or future-oriented work, thereby emphasizing the supposition that the future is always uncertain (see e. g. Allen et al., 2017). In view of this, it is important to stress that analyses of future trends including general future skill trends and changes within the context of the world of work typically entail a degree of uncertainty (Patscha et al., 2017). Thus, due to its forward-looking approach that typically reflects an uncertain future and consistent with other work in this research domain (see e. g. Z-punkt The Foresight Company, 2014), this thesis does not seek to provide definite answers to the questions raised or even make specific predictions about possible future scenarios, but rather aims to provoke debate and thinking about this highly relevant topic of the changing nature of work in general and the future skill demands and changes in particular as a result of job automation. Thus, by conducting an in-depth literature review combined with a qualitative research study in the form of expert interviews to complement and enrich the findings obtained from the literature, the present work hopes to increase existing knowledge regarding anticipated changes in the skill requirements of jobs in the context of increasingly automated work environments. Overall, the present work not only seeks to provide valuable insights regarding anticipated changes in the skill requirements of jobs within the context of automation that are likely to unfold within the next few years across advanced economies, but also aims to elaborate the underlying factors and dynamics that are causing the expected shifts in expected future skill trends and changes. This being said, a number of contributions that the present work seeks to make will be provided in the following.

To start with, the present work along with its theoretical and empirical findings may inform decisions not only of individuals and businesses about current and future skills investment, but also inform and educate policy makers along with education and training providers about future skill needs. In view of this, the Foundation for Young Australians (FYA) (2017) noted that, through gaining information and knowledge concerning the types of skills that will be most valuable for workers to possess in order to succeed in increasingly automated workplaces of the future, individuals can effectively prepare themselves by acquiring and developing the relevant skills of the future. With regard to this, Hajkowicz et al. (2016) argued that individuals, who are planning to make essential decisions concerning future skill and educational investments, should have sufficient information and knowledge in terms of the skill requirements of future jobs. In relation to these aforementioned points, Dawson (2017) emphasized that it will be crucial for individuals to be their very own futurists. With regard to this, Dawson (2017) noted that in a dynamic and constantly changing world of work, it will be important for workers to acquire sufficient information and knowledge concerning the skills of the future that are expected to become increasingly relevant within the coming years. Thus, it is of high importance for individuals to know which kind of skills that they may be investing in and developing will still be valuable and relevant in the next few decades (Dawson, 2017). Underlining the aforementioned points, Engler et al. (2018) stressed that adequate transparency in terms of skill requirements of jobs is essential in order for job seekers to make informed decisions regarding their future career paths. Moreover, Dawson (2017) stressed that, in order for organizations and businesses to remain successful and to continue thriving in this fast-paced world of work powered by sophisticated automation technologies, it will be essential for them to acquire a clear understanding and picture of the future job roles along with their associated skill requirements. In this regard, Bughin et al. (2018) pointed out that seeking to anticipate the shifts in skill demands associated with the adoption and implementation of sophisticated automation technologies into the work environment may provide businesses, governments and other stakeholders with the opportunity to adequately respond and adjust to the expected changes and challenges brought about by automation. In view of this, Kirchherr et al. (2018) argued that obtaining a more thorough understanding of future skill trends and needs is essential as this may not only benefit the decision-making of companies but may also constitute a valuable information basis for educational institutions. In relation to the points mentioned above, Siekmann and Fowler (2017) emphasized that policies that are implemented with the objective to mitigate skill gaps and to adequately prepare current and future workers for future skill demands can be me much more effective when they are based on reliable, timely, and appropriate information with regards to future skill trends. With regard to this, Cedefop (2019) argued that, in order for policymakers and businesses to harness the opportunities while, at the same time, alleviate the risks associated with changes in skill requirements of jobs, timely and relevant information regarding anticipated future trends in terms of the skill needs is required (Cedefop, 2019). In other words, "understanding change is crucial to dealing with it" (Cedefop, 2019, p. 4). All in all, while it is acknowledged that a number of foresight studies addressing the topic centering around future skill trends in the context of job automation already exist, the accelerating pace of change of ongoing technological change in the context of automation calls for a renewed exploration of how sophisticated automation technologies shape future skill trends and changes. In view of this, the present work seeks to further contribute to the existing knowledge and understanding about this highly important topic by aiming to yield additional interesting, valuable, as well as new and timely insights that, in turn, as already discussed above, may contribute to the informed decision-making of various stakeholders.

1.5 Overview of the Structure

The present thesis comprises five main chapters that are further subdivided into different sections, which all build on one another and thus, follow a main red thread. In the following, a short overview of the structure is given.

To start with, the first chapter introduces the central research topic of the present thesis by providing relevant background information to the topic at hand and by presenting the problem statement along with the central research question the present work seeks to answer. Further, an overview of the data collection methods utilized in the realm of this work is provided and the relevance of the research topic along with its potential contribution are discussed. This introductory chapter is then followed by the second chapter that presents the extensive literature review conducted for the purpose of contributing to answering the central research question of the present thesis. The first sub-chapter of the second chapter does not only provide an overview of the concept of automation within the context of the fourth industrial revolution as well as of prevalent modern automation technologies, but also shortly addresses the current debate about the potential impact of this new wave of automation on future employment and jobs. The second sub-chapter builds on the insights outlined in Chapter 2.1 by providing an extensive literature review concerning relevant forward-looking studies that address the concept of job automation and its anticipated implications for employment and the nature of work. Chapter 2.3 then continues by exploring and discussing important determinants of a job's susceptibility to automation as important implications for anticipated future skill trends and changes in the skill requirements of jobs can be drawn from these insights. The extensive literature review then proceeds by outlining the varying effects of automation on jobs due to their important implications for future skill trends and demand, and, based on this, will then present in detail the anticipated future skill trends and demand within the context of increasingly automated work environments as identified by extant literature. Thus, the comprehensive literature review presented in Chapter 2.4 will highlight future skill trends that are anticipated to unfold within the coming decades due to the expected ongoing impact of automation on work and jobs across advanced economies, thereby changing the skill requirements accordingly. Chapter three then presents and outlines the qualitative research study conducted in the realm of the present work in order to enrich and complement the findings derived from the literature with regard to anticipated future skill trends, changes, and demand. Thus, by seeking to complement and enrich the literature findings presented in the realm of this thesis, the qualitative research study aims to allow for a more comprehensive and richer exploration of future skill trends and demand within the context of automation. The in-depth discussion which is then outlined in chapter four will synthesize the findings from both the relevant literature as well as the expert interviews in order to yield a thorough conclusion with regard to the central research question of this work. Within this context, a number of limitations of this work along with some potential future research areas will be presented. The findings obtained by both the extensive literature review as well as the qualitative research study are then used to derive a number of practical implications that are presented in Chapter 4.2. Finally, a concluding chapter is provided at the end of the present work.

2 Literature Review

2.1 The Fourth Industrial Revolution and Job Automation: An Overview

As already indicated above, the present chapter outlines the concept of automation within the context of the fourth industrial revolution along with a number of established modern automation technologies in order to provide the reader with some foundational information and knowledge regarding the central topic on which the present thesis has its focus. Further, the following discussion will also address the current public debate that surrounds this prevalent topic of job automation along with its implications for the nature and future of work, thereby providing a bridge to the discussion that follows in Chapter 2.2.

2.1.1 Automation in the Context of the Fourth Industrial Revolution: Overview of the Concept of Automation and Modern Automation Technologies

A quick glance at past technology-driven transformations of the world of work over the past two centuries reveals that change has always been a substantial and constant part in the world of work (Patscha et al., 2017). For example, the introduction of the steam engine or the assembly line resulted in significant changes that disrupted the working world (Patscha et al., 2017). In addition, the digitalization of the world of work that started already a few decades ago along with the invention of computers initiated further change and transformation within the world of work (Patscha et al., 2017). As remarked by Marion et al. (2020), steam-powered factories that characterized the first industrial revolution, mass-production tools and techniques that represented the second industrial revolution, as well as internet-based technologies that were evident within the context of the third industrial revolution all caused substantial changes in the nature of work (Marion et al., 2020). Nowadays, the world of work is, again, experiencing rapid changes and transformation that are, to a large extent, driven by the adoption, diffusion, and progress of novel sophisticated technologies (Dawson, 2017). In view of this, Marion et al. (2020) argued that, currently, the nature of work is, yet again, undergoing substantial changes due to the ongoing technological progress that is driving the present era of the so-called fourth industrial revolution that is currently taking place. Broadly speaking, the notion of the fourth industrial revolution commonly describes "the potential impact of "cyber-physical systems", which blend hardware, software, and people to complete work" (Collings & McMackin, 2019, p. 12). In view of this, recent progress and advances in modern automation technologies are not only changing the types of jobs human workers perform, but also the way workers are carrying out their jobs (AlphaBeta, 2017). Indeed, sophisticated automation technologies including artificial intelligence and robotics have recently become an increasingly "hot topic" within current media releases and academia (Raj & Seamans, 2019). For example, in October 2017, *Bloomberg Intelligence* released an article arguing that artificial intelligence will likely become the most disruptive force with regards to technology within the next 10 years (Bloomberg Intelligence, 2017; Raj & Seamans, 2019), while, in the same year, the *Financial Times* claimed that the "robot army is transforming the global workplace" (Raj & Seamans, 2019, p. 1). But what exactly is meant by the concept of automation? Broadly speaking, the term automation refers to "the replacement of human beings with machines, robotics or computer systems to carry out an activity" (Frontier Economics, 2018, p. 13). To be more specific, the concept of automation commonly refers to "the use of largely automatic, likely computer-controlled, systems and equipment in manufacturing and production processes that replace some or all of the tasks that previously were done by human labor" (Raj & Seamans, 2019, p. 3). Further, Capita (2019) referred to automation as "the technique, method, or system of operating or controlling a process by highly automatic means, reducing human intervention" (Capita, 2019, p. 29). In addition, AlphaBeta (2017) referred to automation "as the process of using machines to perform tasks that would otherwise be done by humans" (AlphaBeta, 2017, p. 8), while also noting that automation encompasses a wide range of technologies, such as advances in artificial intelligence, robotics, as well as the Internet of Things (AlphaBeta, 2017). As the definitions of automation provided above already indicate, automation may be both partial, which means that only certain distinct work tasks of a given job are automated, as well as complete, whereby the entire range of tasks that a given job encompasses are automated (Lamb et al., 2018).

This being said, within the era of the fourth industrial revolution, organizations are aiming to seize the capacities of modern and sophisticated automation technologies in order to create or increase business value by, for example, achieving greater levels of production efficiency, promoting business growth, or by entering new markets (World Economic Forum (WEF), 2018). In view of this, the following discussion will outline some of the most promising benefits and opportunities associated with the adoption and implementation of automation technologies into the work or business environment (see e. g. Manyika et al., 2017).

Benefits of Job automation

To start with, according to Manyika et al. (2017), the integration of automation into the workplace will allow for the creation of novel forms of competitive advantage as the automation of distinct work activities can significantly increase the performance of nearly any organizational process or practice. Therefore, any of the advantages made possible by automation could constitute a basis of competition (Manyika et al., 2017). A consumer company, for instance, which can deliver more quickly and offer a more rapid customer service around the clock through the adoption of automation in its supply chain and contact centers, may compete in terms of being more reactive and responsive towards its customers (Manyika et al., 2017). In addition, automation may also permit organizations to develop new products, services, or business models. In this regard, a professional services company, for example, may be capable to offer customized advisory services to other companies as well as customers through the means of an automated conversational interface (Manyika et al., 2017). Further, the introduction of advanced automation technologies into the workplace can also yield significant benefits with regard to the organizational performance of the respective companies (Manyika et al., 2017). Besides the benefits cited above, these performance gains may also be realized through higher output, increased quality, enhanced safety, decreased variability, waste reduction, as well as, as already mentioned above, greater customer satisfaction, among other benefits (Manyika et al., 2017). For example, automation entails the capacity to enhance and improve the level of consistency, precision, as well as the customization of a firm's products and services, which, in turn, may allow businesses to meet the demands of their customers in a more effective manner (Lamb et al., 2018). Moreover, the automation of work activities can provide the means to increase organizational performance by, for example, decreasing errors, enhancing quality and speed, and, in some instances, generating outcomes that exceed human capabilities (Manyika et al., 2017). In addition, automation may also raise productivity in organizations (Manyika et al., 2017). In this regard, the researchers found that "automation could accelerate the productivity of the global economy by between 0.8 and 1.4 percent of global GDP annually" (Manyika et al., 2017, p. 25). In terms of the productivity gains resulting from automation, Lamb et al. (2018) argued that through the substitution of specific work tasks for automation, businesses may substantially increase their efficiency with regard to the production of products and services, thereby enhancing their margins and revenue (Lamb et al., 2018).

Further, in light of the aforementioned points, it is important to stress that the benefits of successful adoption and implementation of automation technologies into the work environment do not only relate to capturing the purely economic gains (AlphaBeta, 2017). In fact, automation has the potential to significantly improve the working lives of many individuals as modern automation technologies can take over the most dangerous, tedious, and worst-paid work tasks (AlphaBeta, 2017). As argued by AlphaBeta (2017), automation has the power to make jobs much safer by automating the most dangerous, often physical work tasks. As remarked by AlphaBeta (2017), those work tasks that are among the easiest to be performed by automation technology including arduous physical work activities are usually one of the most dangerous tasks to carry out. In addition, automation has the potential to increase workers' job satisfaction, especially with regard to lower-skilled workers, by performing the most routine, demanding, monotonous and repetitive jobs or work tasks (AlphaBeta, 2017). Lastly, it is expected that, through automation, many jobs will likely become of higher value due to the increasing automation of the least productive work tasks (AlphaBeta, 2017).

Due to the substantial benefits and opportunities for organizations that job automation is expected to effectuate as illustrated above, some experts in the field assume that, in the future, humans and machines will work alongside each other with increasing frequency in order to cultivate the advantages associated with automation technologies, such as increased productivity (see e. g. Neuberger-Fernandez & Barton 2017). In view of this, the general assumption is that, within the near future, modern automation technology will be progressively utilized in all work domains, which, in turn, implies that work, in general, will become increasingly automated (Patscha et al., 2017). As noted by Parry & Battista (2019), workplaces, in general, experience a rapid growth in the adoption and implementation of modern automation technologies, such as artificial intelligence and robotics, in order to automate the more routine and repetitive work tasks and activities including many back-office duties and medical diagnostics with the assistance of predictive algorithms (Parry & Battista, 2019). Consistent with the aforementioned points, the WEF (2020) found that an increasing number of businesses are planning to adopt and implement a variety of automation technologies including artificial intelligence as well as both humanoid and non-humanoid robots. As argued by the WEF (2020), it is expected that both robots and artificial intelligence are steadily becoming a central component within work environments throughout industries, even though the extent of technological adoption differs across industries.

This being said, the following discussion will now focus on widely known types of modern automation technologies and will provide some insights regarding their use-cases.

An overview of modern automation technologies and their exemplary use-cases

To begin with, one of the most prevalent automation technologies of the 21st century presents the concept of artificial intelligence (see e. g. Globerman, 2019; Lamb et al., 2018; Servoz, 2019). As remarked by Globerman (2019), artificial intelligence constitutes a broad-ranging branch of computer science that involves the development of intelligent machines that possess the capacity to execute tasks or activities that usually demand human intelligence. Similarly, Atkinson (2016) noted that artificial intelligence is a constituent of computer science committed to developing computing machines and systems that carry out operations equivalent to human learning and decision-making. Concerning the definition of artificial intelligence, Raj & Seamans (2019) stressed that artificial intelligence presents a concept for which definitions vary and that may be interpreted broadly. As cited in Globerman (2019), Professor John McCarthy, who is widely known as the so-called father of artificial intelligence, defined artificial intelligence as “the science and engineering of making intelligent machines, especially intelligent computer programs” (Globerman, 2019, p. 17), whereas the Association for the Advancement of Artificial Intelligence refers to artificial intelligence as “the scientific understanding of the mechanisms underlying thought and intelligent behavior and their embodiment in machines" (Atkinson, 2016, p. 2). Moreover, Frontier Economics (2018) refers to artificial intelligence as "an umbrella term that describes a suite of technologies that seek to perform tasks usually associated with human intelligence" (Frontier Economics, 2018, p. 13), while Servoz (2019) describes artificial intelligence as "systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals" (Servoz, 2019, p. 22). In this regard, Servoz (2019) noted that artificial intelligence -based systems may be strictly software-based, for instance in the form of conversational assistants or speech and face recognition systems or may be integrated in hardware equipment including robots or autonomous cars (Servoz, 2019).

Further, artificial intelligence can be characterized in a *general* or *narrow* sense (Globerman, 2019; Servoz, 2019). While *narrow* artificial intelligence is typically concerned with carrying out single tasks in a highly sophisticated manner, *general* artificial intelligence enables machines to perform a broad range of problems (Globerman, 2019). As pointed out by Servoz (2019), *general* artificial intelligence refers to "a machine with broad cognitive abilities, which is able to think, or simulate convincingly, all of the human intellectual capacities and potentially surpass them – in practice, it would be intellectually indistinguishable from a human being (Servoz, 2019, p. 24). With regard to the distinction between *general* and *narrow* artificial intelligence, Dellot and Wallace-Stephens (2017) noted that, while *narrow* artificial intelligence refers to "systems that can perform discrete tasks within strict parameters" (Dellot & Wallace-Stephens, 2017, p. 18) including image recognition, natural language processing, information recovery along with reasoning based on logic or evidence, *general* artificial intelligence describes holistic systems that display a level of intelligence that is equivalent or even surpasses that of humans, and thus, are capable of executing all kinds of tasks, such as playing chess or interacting with customers (Dellot & Wallace-Stephens, 2017). Thus, compared to systems predicated on *general* artificial intelligence, *narrow* artificial intelligence systems are restricted in the scope of tasks they are able to execute (Servoz, 2019). In view of this, while the development of *general* artificial intelligence systems featuring human-level intelligence presents the so-called holy grail for numerous artificial intelligence researchers, systems based on *narrow* artificial intelligence are, however, the most sophisticated accomplishment of artificial intelligence technology so far (Globerman, 2019). In relation to this, Dellot and Wallace-Stephens (2017) remarked that the majority of experts hold the belief that the development of artificial intelligence systems possessing a level of intelligence that equals or surpasses the level of human intelligence is still numerous decades away.

Nevertheless, Dellot and Wallace-Stephens (2017) also pointed out that increasing progress is being made in the domain of *narrow* artificial intelligence. This is also underlined by Servoz (2019), who argued that, while artificial intelligence does not present a new phenomenon as already argued earlier, the current rate or speed of its development and advancement constitutes an unprecedented state of affairs.
Overall, based on its various capacities, such as its prediction capacity, artificial intelligence is capable of executing a range of work tasks including analyzing and organizing data, diagnosing diseases, as well as determining and monitoring risks in terms of cybersecurity and financial investing, to name a few (Lamb et al., 2018). With regard to this, as noted by Frontier Economics (2018), artificial intelligence technologies are increasingly utilized in today's business environments, such as in healthcare, where artificial intelligence is assisting in diagnostic decisions or in the creative sectors, where artificial intelligence is employed to create simple news reports about, for instance, specific business results (Frontier Economics, 2018). Moreover, recent progress in the domain of artificial intelligence along with remarkable advances in machine learning, a concept that is discussed in more detail shortly, enable advanced image and speech recognition and result in computers being able to drive cars, trade stocks, recognize fraud, as well as identify speech to respond to basic questions (AlphaBeta, 2017).

To continue, with regard to artificial intelligence, the concept of machine learning presents a particularly interesting variation of artificial intelligence as, through machine learning capacities, machines are capable of going past the performance of basic tasks associated with, for example, sorting and analyzing data executed according to static algorithms designed by human workers and move towards creating and formulating new rules and processes for analysis and decision making premised on the machine's learning from both the data as well as the faults identified in prior iterations of analysis (Lamb et al., 2018). In view of this, Frontier Economics describes machine learning as "a branch of AI that enables computer systems to perform specific tasks intelligently (Frontier Economics, 2018, p. 13). As noted by Frontier Economics (2018), those systems operate complex processes by means of learning from data instead of complying with pre-programmed rules. With regard to this, Dellot and Wallace-Stephens (2017) noted that machine learning techniques operate by training algorithms utilizing available data instead of needing to formulate rules from the ground up. Next, by operating in a reversed manner, the algorithms then identify a specific pattern and, on that basis, develop a generalized rule in order to be able to give meaning to future inputs (Dellot & Wallace-Stephens, 2017). In view of this, the capacity of machine learning systems has substantially progressed in the past few years due to the ever-growing availability of data, sophisticated algorithms in addition to greater computing power (Frontier Economics, 2018). Nowadays, machine learning allows computer systems to perform distinct activities intelligently (Frontier Economics, 2018). In relation to the aforementioned points, Servoz (2019) noted that machine learning involves the capacity to "learn from and improve with experience, without being explicitly programmed" (Servoz, 2019, p. 23). On the basis of adequate data, a machine learning system is able to improve its capacity in providing predictions or in resolving specific problems including recognizing items in pictures (Servoz, 2019).

As pointed out by Frontier Economics (2018), in today's society, individuals are regularly experiencing systems based on machine learning including in the context of voice recognition systems utilized, for instance, by virtual personal assistants. In addition, Dellot and Wallace-Stephens (2017) noted that machine learning systems constitute a prevalent element that is established in all parts of our economy. For example, with regards to the production of media reports, the authors mentioned that a well-known news agency company recently deployed a machine learning software that is capable of generating 3,000 corporate earnings reports per quarter (Dellot & Wallace-Stephens, 2017). In addition, the researchers gave the example of a start-up company called *Fraugster* that utilizes machine learning algorithms to detect fraudulent conduct in financial transactions in just under 15 milliseconds (Dellot & Wallace-Stephens, 2017). Overall, Lamb et al. (2018) argued that the capabilities of machine learning algorithms can be employed across a wide range of sectors, are developed in a way that allows them to constantly refine and advance themselves, and entail the power to promote innovative products, such as autonomous cars (Lamb et al., 2018).

Further, while in recent years advancements in machine learning worked as powerful means to promote significant progress in the field of artificial intelligence, Dellot and Wallace-Stephens (2017) argued that recent emphasis is increasingly placed on deep learning, which constitutes a specific subdomain of machine learning. As noted by Globerman (2019), deep learning constitutes a specific form of machine learning, which enables systems, such as computers, to execute a range of advanced tasks typically performed by humans, such as recognizing or identifying speech or images in addition to producing certain forecasts (Globerman, 2019).

According to Dellot and Wallace-Stephens (2017), deep learning systems consist of artificial neural networks that involve several layers, “with each layer given the task of making sense of a different pattern in images, sounds, or texts” (Dellot & Wallace-Stephens, 2017, p. 20). As remarked by Atkinson (2016), deep learning includes the term *deep* due to its several layers of processing. Against this background, data is then being supplied through several layers which enables the system to classify patterns into different categories, such as objects or words (Dellot & Wallace-Stephens, 2017). In terms of the capabilities of deep learning systems, Atkinson (2016) argued that those systems have the capacity to obtain information and insights out of extensive data sets and subsequently utilize them to ameliorate the performance of a specific task. In relation to this, Servoz (2019) pointed out that deep learning presents a “recent variation of neural networks, which uses many layers of artificial neurons to solve more difficult problems” (Servoz, 2019, p. 23). It is frequently utilized to categorize information derived from images, text, or sound (Servoz, 2019). Further, as pointed out by Allen et al. (2017), recent advances in deep learning algorithms enable artificial intelligence systems to execute tasks associated with financial and legal services, advertising, health diagnostics, surgery, dentistry, as well as veterinary services. In view of the aforementioned points, according to Dellot and Wallace-Stephens (2017), deep learning systems are adopted in many business areas. For instance, with regard to cancer detection, a certain deep learning algorithm designed by the Stanford University has the capacity to identify cancerous skin lesions with the same accuracy as a dermatologist (Dellot & Wallace-Stephens, 2017).

Further, another prevalent automation technology presents the concept of robotics (see e. g. Dellot & Wallace-Stephens, 2017; Raj & Seamans, 2019). As in the case of artificial intelligence, there seems to be no standard definition of a robot (Dellot & Wallace-Stephens, 2017). In view of this, while Dellot and Wallace-Stephens (2017) define robots as “physical machines that move within an environment with a degree of autonomy” (Dellot & Wallace-Stephens, 2017, p. 20), the International Federation of Robotics (IFR) defines an industrial robot as an “automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications” (Raj & Seamans, 2019, p. 2). In view of the latter definition provided above, Raj & Seamans (2019) noted that, while this definition provides a reasonable description for robots for a start, possible other dimensions should be considered when seeking to provide a thorough definition, such as “whether a robot must be automatically controlled or could be autonomous or whether a robot must be reprogrammable" (Raj & Seamans, 2019, p. 2). Broadly speaking, any kind of machine that can be utilized to perform complex tasks or activities automatically may be viewed as a robot (Raj & Seamans, 2019).

Even though robots have been in use within the business and work landscape for decades, the early generations of robots were restricted in their capabilities, which, along with their excessive costs, restricted their overall impact on work (Collings & McMackin, 2019). As noted by Dellot and Wallace-Stephens (2017), whilst robots of the 20th century were usually strongly confined to one single place, the robots of the 21st century are displaying increasing levels of mobility. One key factor that drives the ongoing progress in the field of robotics presents the combinatory use of both artificial intelligence and robotics (Dellot & Wallace-Stephens, 2017). In view of this, even though robots have existed for quite a while, the current generation of robots are increasingly endowed with machine vision and learning capacities that allow them to execute a much wider range of work tasks (GAO, 2019). In relation to this, the OECD (2019b) stressed that, as technology advances, applications, such as artificial intelligence and machine learning, increasingly become an integral part of modern robots, thereby enabling them to become increasingly autonomous and capable to make independent decisions (OECD, 2019b). In this sense, advanced software provides physical machines with the means to manage unexpected conditions or occurrences (Dellot & Wallace-Stephens, 2017). For instance, robots are now being capable of imitating and learning from human workers and of exchanging information or experience with other robots within a network (Dellot & Wallace-Stephens, 2017). Moreover, recent and ongoing developments in robotics are also driven by innovative advances in hardware (Dellot & Wallace-Stephens, 2017). For example, advancements in sensors enable robots to feature the visual awareness required to manage unstructured surroundings (Dellot & Wallace-Stephens, 2017). In relation to the points provided above, Hajkowicz et al. (2016) also stressed that ongoing advances in device connectivity, data volumes, and computing speed, along with significant progress in artificial intelligence systems enable robotic systems to execute a substantial amount of work tasks in a more rapid, secure, and efficient way compared to human workers. These developments in terms of technological capacity, in turn, is reshaping jobs (Hajkowicz et al., 2016).

In terms of the distinction between robotics and artificial intelligence, Raj and Seamans (2019) emphasized that, while robotics or robots typically entail physical manipulation as noted in the definition by the IFR provided above and, thus, are more commonly associated with the automation of physical work tasks, artificial intelligence generally involves computer-based learning as opposed to physical manipulation. Nevertheless, and more importantly, both robotics and artificial intelligence can be employed for the automation of certain work tasks or jobs (Raj & Seamans, 2019). However, the differentiation between these two automation technologies may become blurrier as both concepts may be applied in combination (Raj & Seamans, 2019). For instance, the so-called “smart robots” are based on artificial intelligence or machine learning, which can enhance the robot’s capabilities significantly as already stressed above (Raj & Seamans, 2019). In terms of the capabilities of modern robotics, various robotic applications exist that have noteworthy capabilities. For example, with regard to construction work, a robot named the Semi-Automated Mason (SAM) is capable of arranging as many as 1,200 bricks in one day, which stands in comparison to the 300 to 500 bricks a human worker is able to put in place (Dellot & Wallace-Stephens, 2017). Moreover, the robotics company Starship Technologies has created a robot that is capable of supplying parcels in an autonomous manner and is currently being tested globally by numerous logistics companies (Dellot & Wallace-Stephens, 2017).

As illustrated by the foregoing discussion, the pace of progress in modern automation technologies including artificial intelligence and robotics has accelerated significantly throughout the past few years, thereby allowing an increasing number of work tasks and activities to be performed by automation technology (Dawson, 2017). In view of the insights presented above, the following section will discuss several voices and opinions that address this aforementioned technological change associated with the new wave of automation, thereby constituting an introduction and starting point to the analysis of relevant empirical literature in the field of job automation that follows in Chapter 2.2. Further, as evident throughout the foregoing discussion, the present thesis uses the notion *automation technologies* as a broad term in order to refer to modern technologies that are commonly utilized in modern workplaces to automate certain work tasks, activities, or jobs. Thus, for the purpose of simplicity, the remainder of this thesis will utilize the notion *automation technologies* when seeking to refer to non-specified technologies that have the capacity to automate jobs or distinct work tasks, such as the automation technologies outlined above. While the preceding discussion presented some of the most prevalent automation technologies that are addressed in extant literature, it is important to stress at this point that a wide range of automation technologies exist. However, due to the limited scope of this thesis, the foregoing discussion refrained from providing a comprehensive list of currently existing automation technologies. In addition, for the sake of simplicity, the remainder of this thesis will follow the approach put forward by various scholars and researchers (see e. g. Atkinson, 2018; Chui et al., 2016; Lamb et al., 2018; WEF, 2018) by utilizing the two terms *automation technology* and *automation technologies* when seeking to describe or refer to non-specified technologies that are designed to carry out jobs or distinct work tasks, and, thus, entail the potential for automation.

2.1.2 Current Debate on Automation

In light of the technological progress concerning job automation illustrated above, a number of voices in the current public debate have expressed their concerns that such technological developments associated with this new wave of automation will result in a great amount of people losing their jobs due to displacement by advanced automation technology (Arnold et al., 2018; Arntz et al., 2016; Bakhshi et al., 2017; Mokyr et al., 2015; Servoz, 2019). For example, just recently, well-known entrepreneurs including Elon Musk, who is the founder of Tesla, along with Mark Zuckerberg, who is the founder of Facebook, voiced their concerns that this new wave of automation powered by sophisticated automation technologies, such as artificial intelligence, will effectuate wide-scale unemployment based on the rationale that these technologies predicated on human-like intelligence have the capacity to execute the activities usually performed by humans with a much greater efficiency (Globerman, 2019). In addition, as already mentioned above, recent provocative media headlines (see e. g. Aratani, 2020; Taylor, 2019) potentially further instigate the fear of widespread job destruction caused by sophisticated automation technology.

However, such technological anxiety does not present a novel phenomenon as fears of technological unemployment have been voiced in the past (Bakhshi et al., 2017; Mokyr et al., 2015). For example, in the past, leading thinkers including David Ricardo, Karl Marx, and John Maynard Keynes expressed their concerns about the impact of technological progress in terms of automation on employment (Manyika, Lund, Chui, et al., 2017). While David Ricardo, a political economist, raised concerns in the early 19th century that machines would render human labor redundant, in the 1850s, Karl Marx anticipated an “era when the means of labor would be transformed by “an automatic system of machinery” (Manyika, Lund, Chui, et al., 2017, p. 33). Further, in 1930, John Maynard Keynes cited the notion of *technological unemployment* to refer to “a situation in which innovation that economized on the use of labor outstripped the pace at which new jobs could be created” (Manyika, Lund, Chui, et al., 2017, p. 33). A few decades later, as technology progressed, fears again were voiced concerning whether new automation technologies would herald "the end of work" as worded by the US economist Jeremy Rifkin in the year 1995 (Frontier Economics, 2018). Nevertheless, even though past periods of technological change within the context of automation caused significant disruptions to the overall nature of work as already mentioned earlier (Marion et al., 2020), no mass unemployment resulted from automation (Khurana, 2018; Zeira & Nakamura, 2018). In view of this, Tytler et al. (2019) pointed out that, while stating that making predictions about the future based exclusively on past occurrences is neither desirable nor possible, but that it is, nevertheless, essential to consider that humans have been raising concerns about the potential destructive impact of automation throughout the past few centuries, none of their dire predictions about technology-induced mass unemployment have come true (Tytler et al., 2019). Overall, as noted by Manyika, Lund, Chui, et al. (2017), in the past, technological change led to new job creation that exceeded the number of jobs made redundant by technology, fostered an increase in productivity and living standards, and resulted in a shift concerning the balance between work and leisure time (Manyika, Lund, Chui, et al., 2017). Thus, even though workers and industries needed to adjust to the changes brought about by technological change, over the longer term, fears about wide-scale technological unemployment were not proven true (Bakhshi et al., 2017).

However, as pointed out by Bakhshi et al. (2017), automation technologies in the past were confined in their capabilities to manual and cognitive routine work tasks predicated on well-defined and repetitive processes. Yet, as illustrated in the previous section, the latest technological advances in automation are increasingly able to emulate, to a certain extent, the human body and mind, thereby being capable to potentially invade a number of non-routine work tasks and activities including legal writing, truck driving, and providing medical diagnoses (Bakhshi et al., 2017). In this regard, Arntz et al. (2016) noted that new fears about technological unemployment are based on the underlying rationale that advanced job automation technologies are increasingly pervading those tasks that usually belong solely to the human domain including reasoning, sensing, and deciding (Arntz et al., 2016). Based on this, concerns arise that this new wave of automation powered by sophisticated technologies, such as artificial intelligence, may potentially significantly affect and displace also high-skilled jobs (Servoz, 2019). Overall, as noted by McKay et al. (2019), increasingly advanced automation technologies may result in a more fast-paced, intensive, wide-scale, and, ultimately, more disruptive automation (McKay et al., 2019). With regard to this, Autor (2014) and McKay et al. (2019) noted that in the past and in line with philosopher Michael Polanyi's statement that "we know more than we can tell" (Autor, 2014, p. 8; McKay et al., 2019), the extent of automation was constrained in the sense that, based on Polanyi's concept, engineers are not able to program a machine to emulate a specific task or process "that they do not explicitly understand" (Autor, 2014, p. 8; McKay et al., 2019). However, recent technological progress allows machines to identify certain data patterns without clear and precise human programming (McKay et al., 2019). In view of the aforementioned points, the fear of technological unemployment due to automation has also recently been ignited by several studies that suggest that a substantial number of jobs are at high risk of being supplanted by automation technologies as will be further discussed in the next chapter (Arnold et al., 2018; Arntz et al., 2016; see e. g. Frey & Osborne, 2013). Frey & Osborne (2013), for example, found that around 47% of workers in the US occupy jobs that possess a very high risk of being automated with the next decade or two (Arnold et al., 2018; Frey & Osborne, 2013).

In light of the arguments above, Servoz (2019) noted that much of the fear concerning the employment effect of sophisticated automation technologies may be caused by the conception that systems based on general artificial intelligence are increasingly pervading today's workplaces, and thus, will be ultimately displacing workers on a large scale (Servoz, 2019). In this regard, even though automation in the past did not cause widespread unemployment, the recent technological advances in domains including artificial intelligence and machine learning that drive the current wave of automation give rise to the question if it is, in fact, different this time (Manyika, Lund, Chui, et al., 2017; Servoz, 2019). With regard to this, while underlining that widespread substitution of labor by automation followed by large-scale unemployment are not likely to occur in the near future, Cedefop (2018) pointed out that the possibility that it may be, in fact, different this time cannot be entirely discarded. In this context, Cedefop (2018) remarked that, contrary to the past, current cycles of technological innovation and progress appear to take place at a much higher rate than in the past and the rapid development in automation is predicted to also affect high-skill occupations comprising non-routine work tasks (Cedefop, 2018).

In view of the aforementioned points, two contrasting viewpoints can generally be identified within current literature addressing the topic of the future of work within the context of automation (Collings & McMackin, 2019). As noted by the WEF (2016), two opposing viewpoints in terms of the employment effects caused by disruptive change within the context of automation have lately emerged. On the one hand, some hold a rather optimistic viewpoint by arguing that rapid technological change within the automation landscape will result in far-reaching opportunities and allow workers to free themselves from doing routine work, while, on the other hand, other, more pessimistic, voices forecast widespread labor substitution and displacement of jobs (WEF, 2016). Similarly, Lamb et al. (2018) remarked that, while one prevalent view envisions a future, in which sophisticated automation technology is increasingly capable to carry out a wide range of distinct jobs and work tasks, thereby making a large number of workers redundant, the other view with regard to the future world of work and automation sees automation as providing, over the longer term, a huge opportunity to increase productivity levels and competitiveness, as well as promoting employment growth (Lamb et al., 2018). In terms of the more pessimistic outlook concerning the future world of work, a number of current voices put forward the argument that, despite the reassurance from history that widespread unemployment due to automation is unlikely to occur in the near future, this new wave of automation powered by sophisticated technologies will be different to the ones in the past by claiming that automation in the coming years will be much more disruptive to workers than it was in the past (Manyika, Lund, Chui, et al., 2017; see e.g. Brynjolfsson & McAfee, 2014). Nevertheless, in relation to the points mentioned above, it should be stressed at this point that there are various factors that must be considered when talking about possible future scenarios with regard to the world of work in the context of increasingly automated work environments (see e. g. Arntz et al., 2016; Manyika et al., 2017; Oschinski & Wyonch, 2017). For example, as pointed out by Oschinski & Wyonch (2017), an important aspect to consider in this context is that general automation potential should not necessarily be interpreted as actual automation as the path to actual automation strongly depends on a variety of factors. In view of this, the literature acknowledges a number of factors that have the potential to significantly influence and constrain the pace and extent of the adoption and implementation of modern automation technologies (see e. g. Manyika et al., 2017). Manyika et al. (2017), for example, pointed out that, even though technology is progressing continuously, the path from mere technical automation potential towards comprehensive and large-scale adoption will, nevertheless, likely require decades. In this regard, the authors assume that adoption commences when the designed technology solution for any given work activity equals or is beneath the cost for human workers to execute the respective activity in a certain occupation. In this context, the authors maintained that this transitory period from sheer technical automation potential to thorough adoption is influenced by a number of different factors (Manyika et al., 2017).

The first factor regards the technical feasibility. In this sense, the implementation of technology into the workplace is viable only when the required technologies can display the necessary level of performance in terms of the capabilities needed to execute specific work activities (Manyika et al., 2017). Despite the fact that certain machines or technologies already meet or even surpass the human level of performance regarding certain capabilities, there still exist various capabilities that demand further technological development (Manyika et al., 2017). This is also underlined by Dellot and Wallace-Stephens (2017), who argued that, although the capacity of modern technology advanced significantly in the past few years, there still exist many things that these systems are, to date, not capable of doing. In this respect, substantial progress in, for example, natural language-understanding or emotional and social reasoning capacities has the potential to considerably enlarge the technical automation potential (Manyika et al., 2017). However, it is essential to recognize that sheer technical feasibility does not necessarily translate into actual implementation of the respective automation technology, which, as the following discussion will show, also depends on various other factors (Manyika et al., 2017). Besides the technical feasibility, the cost of automation presents a second factor that largely influences the business case for organizational adoption, and thus, the actual extent or scope of automation (Manyika et al., 2017, van der Zande et al., 2018). Concerning this aspect, van der Zande et al. (2018) noted that organizations are only willing to implement new technologies provided that their benefits outpace their costs (van der Zande et al., 2018). As argued by Lamb et al. (2018), in the case when the relative costs of human labor surpass the costs of technology adoption and implementation, business will prioritize automation technology to perform the respective jobs or work tasks. Another factor to consider in this context is the labor cost and associated supply and demand dynamics. In the case that human workers are of ample supply and consequently considerably less cost-intensive than automation, then this would present a substantial argument against technology adoption for each respective organization (Manyika et al., 2017). Moreover, even when the implementation of automation technologies into the workplace constitutes a business imperative in order to increase overall organizational performance, the extent of adoption may be influenced by context-dependent factors relating to regulatory and social acceptance (Manyika et al., 2017). For example, transforming organizational processes and practices to accommodate the new technologies may require a lot of time. In addition, government policies may delay adoption, and different organizations may establish certain technologies at differing pace. Apart from this, humans may display discomfort concerning situations, in which machines substitute human interaction, especially in various private or personal surroundings or circumstances, such as hospital settings. For example, a robot may technically be capable to perform some of the work tasks usually done by a nurse, but this may be experienced as offensive and inacceptable by many patients, who both expect and trust human interaction (Manyika et al., 2017). In line with the arguments put forward by Manyika et al. (2017), Arntz et al. (2016) also asserted that the assumed proportion of jobs at risk due to automation must not be likened to actual job losses effectuated by advanced automation technologies. In view of this, Arntz et al. (2016) noted that the implementation of new technologies may present a rather slow process by reason of certain economic, legal, and societal constraints, as already indicated by Manyika et al. (2017). Consequently, the full extent of technologies' replacement of work tasks may not happen as originally predicted or expected (Arntz et al., 2016).

The factors discussed above often represent significant barriers to the automation of work as these have the potential to substantially impede the adoption of new technologies into the workplace (Maynika et al., 2017; van der Zande et al., 2018). Thus, the speed at which automation is established within a certain sector or occupation mirrors the interplay of various distinct factors (Manyika et al., 2017). This is also underlined by Servoz (2019), who argued that the extent to which employment or labor markets in general will be affected by automation also is dependent upon the scope and pace of the adoption of modern automation technologies, which, as the discussion above illustrates, depends on various different factors that may significantly impede the adoption and diffusion of automation technology (Maynika et al., 2017; Servoz, 2019; van der Zande et al., 2018). In addition, even when automation is taking place, there may be different additional dynamics mitigating the possible negative effects of automation, such as switching to less automatable work tasks (Arntz et al., 2016). With regard to this, Arntz et al. (2016) pointed out that, even in the case when new technologies are, in fact, established within the workplace, workers may adapt to these changes by shifting towards other work tasks, thereby avoiding technological unemployment (Arntz et al., 2016). Thus, as noted by Arntz et al. (2016), workers may be able to relocate from routine and other easily automatable tasks towards tasks more complementary to automation technology. Consequently, as argued by Arntz et al. (2016), provided that workers are capable to adapt to the newly required task demands, the risk to be displaced by technology decreases significantly (Arntz et al., 2016). Further, in spite of the fact that modern automation technologies including artificial intelligence and robotics have the capabilities to automate a range of work tasks, activities or jobs hitherto performed by human workers, this does not necessarily suggest that the workers that are affected by automation will be out of work (Raj & Seamans, 2019). As will be discussed more thoroughly in Chapter 2.4.1, the automation of certain low-value work tasks may allow human workers to focus more heavily on high-value work tasks (Raj & Seamans, 2019). In view of this, automation may result in the so-called augmentation of work carried out by human labor (Raj & Seamans, 2019).

In view of the arguments provided throughout this section regarding the effect and impact of modern automation technologies on work, jobs, and employment, Frontier Economics (2018) emphasized that, while sophisticated automation technologies, such as artificial intelligence, are not likely to effectuate the "end of work", they, nevertheless, are expected to cause significant changes to the world of work as the following chapters of this thesis will illustrate. As stressed by Lamb et al. (2018), while automation may not eradicate employment, it is, nevertheless, expected to significantly shape and transform the nature of work as well as the skills required. These aspects will be thoroughly discussed and investigated throughout the remainder of this thesis. In light of this, the subsequent chapter will discuss in detail current evidence regarding the anticipated future impact of automation on employment and thereby aims to contribute to a clearer understanding of the anticipated effects of the current wave of automation. At the same time, this literature synthesis and its corresponding findings serve to produce a valuable knowledge base that assists in understanding the dynamics underlying the central topic of thesis and thereby seek to provide the essential first step in answering the central research question of the present thesis.

Summary of the chapter

Along with introducing the prevalent concept of job automation within the context of the fourth industrial revolution, the present chapter provided a short overview of a number of widely cited modern automation technologies and highlighted some of their applications and use cases within the current business environment. In addition, the foregoing discussion addressed the current public debate about the impact of this new wave of automation powered by sophisticated technologies on future employment and jobs, thereby bringing attention to popular and often contradicting opinions about this subject matter. The subsequent chapter will build on these insights by seeking to provide a clearer picture concerning the effects of job automation expected in the near future by analyzing a set of dominant and relevant studies in this research field. At the same time, the findings presented in the following chapter provide the knowledge base for answering the central research question of this thesis.

2.2 Job Automation and its Anticipated Implications for Employment and the Nature of Work: Presentation and Assessment of Relevant Studies

Driven by the technological progress and changes within the context of job automation as discussed in the previous chapter, numerous forward-looking studies have been published over the past few years that aimed to estimate or assess the potential risk of automation for future jobs and work in general, thereby seeking to explore the disruptive potential of automation (Arntz et al., 2016; Manyika et al., 2017; Frey & Osborne, 2013; McKay et al., 2019; Patscha et al., 2017). While some of the points discussed in the foregoing chapter seem to suggest that widespread technological unemployment induced by ongoing advances in automation is unlikely to occur within the near future (see e. g. Frontier Economics, 2018; Lamb et al., 2018), Bessen et al. (2020) stressed that "the actual impact of automation is an empirical matter" (Bessen et al., 2020, p. 7). Consequently, the present chapter will provide an in-depth overview of recent empirical evidence regarding the potential future impact of job automation on employment in order to enlarge the reader's understanding of this matter. This discussion will then be followed by a detailed analysis of determinants of job automation risk in order to better comprehend the distinct variables that determine the risk of automation for a given job. This in-depth literature review will serve as a valuable foundation for the subsequent discussion that follows in Chapter 2.4, which will address in detail the above-cited central research question of the present thesis.

2.2.1 The Substitution Effect of Automation

The subsequent discussion will provide an in-depth analysis of dominant studies addressing the impact of job automation on employment. While it is acknowledged that there are different effects to consider when seeking to depict a comprehensive picture of the overall impact of job automation on employment as will be further discussed later in this section, the following discussion will have its particular focus on the substitution effect of automation due to the limited scope of this thesis. As already mentioned earlier, the substitution effect refers to the situation, in which human workers are replaced by automation and thus, the adoption and implementation of modern automation technologies work as a substitute for human workers (Frontier Economics, 2018). In view of this, while some scholars make use of the term *substitution effect* (see e. g. Arntz et al., 2016; Autor, 2015; Cedefop, 2017), others prefer the term *displacement effect* (see e. g. Acemoglu & Restrepo, 2019; Dahlin, 2019) while referring to the situation, in which modern automation technologies, such as robots, are replacing human workers (Dahlin, 2019). Due to the fact that, in extant literature, those two terms are both regularly utilized to refer to the same situation as described above (see e. g. Acemoglu & Restrepo, 2019; Arntz et al., 2016; Dahlin, 2019), the present work will use these terms interchangeably. In addition, as illustrated by the current literature (see e. g. Manyika et al., 2017), the notions of jobs and occupations are often used interchangeably and commonly refer to "the specific role a person performs" (FYA, 2017, p. 8), and to "a set of tasks that can be performed either by a human or by technology or a combination of both" (Oschinski & Wyonch, 2017, p. 3). Moreover, work activities or work tasks may refer to "the application of skill and knowledge to complete a goal" (Oschinski & Wyonch, 2017, p. 3) and to the chores or functions workers carry out within the realm of their jobs or occupations, such as collecting information or analyzing data (FYA, 2017). Further, the notion of *skills* refers to "the capacity required to perform an activity" (FYA, 2017, p. 8) and to "an ability, whether learned or inherent, that facilitates the learning, acquisition and application of knowledge" (Oschinski & Wyonch, 2017, p. 3), and workers generally deploy multiple skills at once in order to execute a specific work task (FYA, 2017).

2.2.2 Studies Utilizing an Occupation-Based Approach

Concerning the assessment of the impact of advanced automation technologies, the often-cited and much-debated seminal research study conducted by Frey & Osborne (2013) was among the first that aimed to estimate in quantifiable terms the impact of recent technological advances in automation technology on future employment (Frey & Osborne, 2013; Frontier Economics, 2018; Vazquez et al., 2019). In their renowned research study, Frey & Osborne (2013) explored the susceptibility of jobs in the US labor market to automation given recent progress in machine learning and mobile robotics. More specifically, the researchers sought to assess the risk of automation for 702 detailed occupations based on a technological capability perspective (Frey & Osborne, 2013). Thus, they did not take into account political or social dynamics that may affect the adoption and implementation of automation technology (Pajarinen & Rouvinen, 2014).

In view of this, the analysis performed by Frey & Osborne encompassed four different steps (Elliot, 2017; Frey & Osborne, 2013). The first step comprised the categorization of 70 distinct occupations as either automatable or not automatable. This activity was performed by a group of machine-learning experts on the basis of specific job descriptions as well as their knowledge regarding technological capabilities (Elliot, 2017; Frey & Osborne, 2013). The selected set of 70 occupations constituted those where the experts were highly confident in making appraisals regarding their automatability (Elliot, 2017; Frey & Osborne, 2013). In a second step, Frey & Osborne (2013) identified so-called engineering bottlenecks to automation, which also can be referred to as barriers to automation, that correspond to three distinct task categorizations, and which, according to Frey and Osborne (2013), determine the degree or magnitude of job automation in the twenty-first century (Elliot, 2017; Frey & Osborne, 2013). In this regard, these identified bottlenecks to automation encompass the domains of perception and manipulation, creative intelligence, as well as social intelligence (Frey & Osborne, 2013). However, as noted by Oschinski and Wyonch (2017), great technological progress has been made with regard to the domain of perception and manipulation, and therefore, this domain originally identified as an engineering bottleneck no longer constitutes an area of exclusive human superiority according to Oschinski and Wyonch (2017). This being said, in addition, Frey and Osborne (2013) identified nine different variables derived from the O*NET (Occupational Information Network) database that correspond to these distinct bottleneck categories. First, the variables corresponding to perception and manipulation encompass finger and manual dexterity as well as cramped workspace and awkward positions. Further, the factors associated with creative intelligence include originality and fine arts. Lastly, the variables closely related to social intelligence include social perceptiveness, negotiation, persuasion, as well as assisting and caring for others (Frey & Osborne, 2013). In light of this, while, as already argued earlier, sophisticated automation technologies are expected to be increasingly able to perform several non-routine tasks, Frey & Osborne (2013) argued that jobs characterized by a high degree of those bottleneck tasks cited above are relatively secure from being automated by advanced technology in the near future (Frey & Osborne, 2013). In other words, "the probability of an occupation being automated can thus be described as a function of these task characteristics (Frey & Osborne, 2013, p. 262). On these grounds, Frey and Osborne (2013) investigated the susceptibility of jobs to automation as a function of the bottleneck tasks cited above. In a third step, occupational data on the distinct variables corresponding to these three groups of bottlenecks were utilized in order to establish a model to first, predict the probability of automation for the 70 chosen occupations, and second, to then apply this model to predict the automatability for all 702 US occupations assessed in the context of the study (Elliot, 2017; Frey & Osborne, 2013). In a last step, Frey and Osborne (2013) categorized jobs according to their susceptibility to automation by, given their probability of automation, distinguishing between low, medium, and high-risk occupations (Elliot, 2017; Frey & Osborne, 2013). In this regard, the researchers categorized occupations, which exhibit a probability of automation under 30% as low risk, and those, which feature a probability of over 70% as high-risk occupations (Frey & Osborne, 2013).

Based on the analysis discussed above, the researchers found that 47% of jobs in the US are attributed a high risk of automation, which, as mentioned earlier, corresponds to an automation probability of at least 70%, and thus, according to the researchers, are highly likely be automated in the next decade or two (Frey & Osborne, 2013; Vazquez et al., 2019). This finding illustrates that recent technological developments in automation technology are potentially threatening a significant portion of occupations in the near future (Frey & Osborne, 2013). However, it should be noted at this point that the researchers explicitly argued that they did not aim at providing an estimate concerning the share of jobs that will, in fact, be automated, but rather solely considered the potential of job automation (Frey & Osborne, 2013).

As indicated earlier, the research study conducted by Frey and Osborne (2013) incited a rich public debate and motivated other scholars and researchers to examine this research subject in question further (Frontier Economics, 2018). Hence, the findings publicized by Frey and Osborne (2013) spurred a number of follow-up studies, which applied the methodology proposed by Frey & Osborne (2013) to other countries (see e. g. Bowles, 2014; Bonin et al., 2015; Brzeski & Burk, 2015; Pajarinen & Rouvinen, 2014). Bonin et al. (2015) and Brzeski and Burk (2015), for example, applied the findings derived by Frey & Osborne (2013) to Germany to estimate the number of jobs at risk of automation and found that, respectively, 42% and 59% of jobs in the German labor market are at high risk of being automated in the near future (Bonin et al., 2015; Brzeski & Burk, 2015). In addition, two other research studies transferred the results yielded by Frey and Osborne (2013) to Finland (Pajarinen & Rouvinen, 2014) and Europe (Bowles, 2014). In this regard, while Pajarinen and Rouvinen (2014) concluded that around 35% of Finnish employment pertains to the high-risk category of potential automation, Bowles (2014) found that, on average, 54% of jobs in the European labor market are at high risk of automation.

2.2.3 Critique of the Occupation-Based Approach

As already mentioned earlier, the studies' findings presented above significantly contributed to the rise of fear of large-scale unemployment due to sophisticated job automation technologies and thereby played a significant part in instigating a public debate about the effects of job automation on employment (Arnold et al., 2018). In addition, the above-cited studies, which follow an occupation-based approach, are often criticized by other scholars due to the fact that it can be assumed that the numbers reported in those studies greatly overestimate the number of jobs that are at high risk of being automated in the years to come (Arnold et al., 2018). In view of this, a number of researchers argued that such occupation-level studies greatly exaggerate and overestimate automation potentials due to a number of reasons (see e. g. Arntz et al., 2016; Dahlin, 2019; Goos et al., 2019). In this regard, Arntz et al. (2016), for example, stressed that one of the major weaknesses of the occupation-based approach is that it follows the assumption that occupations tend to be similar across countries (Arntz et al., 2016). Moreover, Arntz et al. (2016) pointed out that, by basing their methods on the level of occupations, researchers that follow this approach (see e. g. Frey & Osborne, 2013) thereby assume that workers operating within the same occupations possess identical task structures (Arntz et al., 2016). However, as noted by Autor and Handel (2013), the task structures of workers vary significantly within occupations (Arntz et al., 2016; Autor & Handel, 2013). Consequently, it can be assumed that workers are possibly quite differently affected by automation technologies depending on the work tasks carried out by the workers, not only across occupations, but even within them (Arntz et al., 2016). In line with this, Arnold et al. (2018) pointed out that not all tasks within a given job possess the same automation potential as some work tasks can be easily performed by advanced technology, others, however, prove to be more difficult to being automated. Thus, "whether an occupation can be automated or not depends on how significant the type of tasks are that can be carried out by machines" (Arnold et al., 2018, p. 76). This point is also underlined by Dahlin (2019), who stressed that nearly every job or occupation encompasses a variety of heterogeneous work tasks, of which some tasks can be characterized as routine tasks while others cannot. According to Dahlin (2019), nearly all jobs involve both types of tasks, routine as well as non-routine, irrespective of whether the job or occupation is characterized as high-skill, middle-skill, or low-skill. Thus, the assessed probability in terms of the automation risk or potential of an entire occupation is generally overestimated (Dahlin, 2019). As a result, as argued by Arntz et al. (2016), the potential of automation can differ significantly between jobs, even within identical occupational groups (Arnold et al., 2018). Consistent with the arguments above, Nedelkoska and Quintini (2018) asserted that jobs vary substantially within occupations with regard to their work tasks and that "valuable information is lost when the risk of automation is calculated based on the skill requirements of broad occupational categories (Nedelkoska & Quintini, 2018, p. 48). All in all, task-based analyses can generate much more in-depth information compared with occupational analyses (Schulte & Howard, 2019).

2.2.4 Studies Utilizing a Task-Based Approach

In view of the above-cited critique of the occupation-based approach, a variety of researchers conducted a number of follow-up studies making use of a more granular approach by focusing on the level of tasks or work activities in order to capture exactly this heterogeneity of tasks across and within occupations disregarded by the occupation-based approach (see e. g. Arntz et al., 2016; Manyika et al., 2017; Nedelkoska & Quintini, 2018). As already mentioned earlier, a task refers to "the application of skill and knowledge to complete a goal" (Oschinski & Wyonch, 2017, p. 3) and to the chores or functions workers carry out within the realm of their jobs or occupations, such as collecting information or analyzing data (FYA, 2017). With regard to this, as further pointed out by Oschinski and Wyonch (2017), in the case that a task merely demands procedural skills, the respective tasks is routine in nature. On the contrary, if a task demands rather abstract skills, the specific task can then be characterized as non-routine as the respective procedure may differ in some abstract way in order to accomplish the set goal (Oschinski & Wyonch, 2017). In this sense, subsequent studies emerged based on the rationale that occupations are made up of a bundle of distinct tasks, of which some can potentially be automated while others cannot (Autor, 2015; Frontier Economics, 2018; Oschinski & Wyonch, 2017). Thus, as already indicated above, such a task-based approach is founded on the underlying notion that the automatability of jobs eventually is determined by the work tasks that workers conduct as part of their respective job, as well as on the ease with which these tasks could be automated (Arntz et al., 2016). In view of this, the following discussion will provide an in-depth analysis of a number of recent studies that sought to assess the substitution effect of job automation on employment by adopting the above-mentioned task-based approach.

In their report, which was developed as part of the McKinsey Global Institute's comprehensive research on the impact of technology on business and society**,** Manyika et al. (2017) examined the potential of currently established automation technologies, given their technical feasibility, to automate a wide range of work activities, utilizing data from the US Bureau of Labor Statistics and O*NET. In particular, the authors established the state of technology with regard to 18 performance capabilities to assess the technical automation potential of approximately 2,000 work activities relating to roughly 800 occupations across the US economy, and then expanded their analysis across 45 different other countries, making use of the best-fitting corresponding data accessible for each country (Manyika et al., 2017). It's of importance to note that, when the researchers made use of the term automation potential in their report, they were referring to the technical automation potential of currently available technologies. As already elaborated above, the mere technical feasibility of a specific technology is not equivalent to actual automation, which, as illustrated earlier, also depends on various other factors (Manyika et al., 2017). In this sense, as argued by Chui et al. (2016), "technical feasibility is a necessary precondition for automation, but not a complete predictor that an activity will be automated" (Chui et al., 2016, p. 2). While the authors included a wide range of automation technologies into their perspective, Manyika et al. (2017) explicitly mentioned that they do, however, not fixate on any precise technologies. In their report, the authors provided a non-exhaustive listing of various technologies utilized to allow the automation of distinct work activities, including artificial intelligence and its subfield machine learning, neural networks, and robotics (Manyika et al., 2017). While some of the studies presented earlier based their analysis on the level of occupations (see e. g. Frey & Osborne, 2013), in Manyika et al. (2017), the level of analysis constitutes distinct work activities as opposed to entire occupations. Their decision to focus on the level of work activities is based on the argument that the authors regard work activities as a more relevant and appropriate measure due to the fact that occupations consist of various activities, which all hold a diverse automation potential (Manyika et al., 2017).

Based on their analysis of about 2,000 work activities across 800 occupations, the authors found that, given currently demonstrated technology, 49% or, in other words, approximately half of the activities, which individuals are compensated for in the global economy, could potentially be automated. Adding to this appraisal, the authors concluded that only approximately five percent of the entire occupations can be automated completely, while nearly 60 percent of all occupations contain at least 30 percent of constituent activities that could be performed by currently established automation technology. Thus, Manyika et al. (2017) found that the share of occupations, in which all of the work activities relating to a specific occupation can be automated entirely through the adoption of currently established technology, constitutes a notably small amount of just five percent. Nevertheless, the authors also pointed out that, based on their findings, automation will, to a larger or smaller degree, have an impact on nearly all occupations. Regarding this observation, Manyika et al. (2017) emphasized that the potential for automation of each distinct occupation depends on the specific work activities the respective occupation encompasses (Manyika et al., 2017). Based on these findings, the authors concluded that the majority of occupations will rather undergo substantial changes than just being automated away (Manyika et al., 2017). This is consistent with the argument provided by the Foundation for Young Australians (FYA), which stressed that, while certain jobs will likely experience a decline or growth due to automation, too much emphasis has been put on predictions regarding which jobs will diminish as a result of automation and which will continue to exist (FYA, 2017). In fact, the FYA argued that, in reality, automation will affect all kinds of jobs to a certain degree (FYA, 2017). Thus, according to the FYA (2017), it is a misconception to believe or to expect that only certain jobs will be affected while other jobs remain untouched by automation.

Another relevant study addressing the realm of job automation in the context of the future of work presents the research conducted by Arntz et al. (2016). Arntz et al. (2016) assessed the job automation potential for jobs in 21 OECD countries by largely placing their method on the approach presented by Frey and Osborne (2013) as discussed above. However, rather than following the assumption that it is entire occupations that may be supplanted by automation technology, the researchers took a task-based approach as, according to the authors, it is distinct tasks as opposed to whole occupations that are displaced by technology (Arntz et al., 2016). In particular, the researchers made use of individual-level data in the form of individual survey data concerning an extensive list of work tasks that workers actually conduct in the realm of their workplace in order to take into consideration the underlying rationale that individual workers within the same occupation in many times carry out fairly distinct tasks (Arntz et al., 2016). Thus, unlike other studies that followed an occupation-based approach (see e. g. Frey & Osborne, 2013), the researchers took into consideration the heterogeneity of work tasks across countries as well as within occupations (Arntz et al., 2016). From that perspective, Arntz et al. (2016) anticipated that those occupations at high risk of automation, as concluded by Frey and Osborne (2013), might have a significantly lower automation potential when taking into account the fact that the majority of occupations comprise work tasks that prove to be highly difficult to automate (Arntz et al., 2016). With regard to this, the authors found that “on average across the 21 OECD countries, 9% of jobs are automatable” (Arntz et al., 2016, p. 4), a number considerably lower than the one identified by Frey and Osborne (2013). In this regard, while Frey and Osborne (2013) found that 47% of jobs in the US could be automated, the corresponding number identified by Arntz et al. (2016) is only 9%. Hence, this finding provides a stark contrast to the figure determined by Frey and Osborne (2013) and suggests that, clearly, not taking into consideration the heterogeneity of tasks within occupations significantly influences the assessed automatability of jobs (Arntz et al., 2016). This argument is consistent with the findings obtained by Bonin et al. (2015), who found that, when following an occupation-based approach as pursued by Frey & Osborne (2013), that 42% of jobs in the German labor market are at high risk of automation. However, as it is mostly tasks and not whole occupations that could potentially be automated, the researchers provided an alternative approach by focusing their analysis on distinct tasks of the respective occupations and found that only around 12% of jobs are attributed a high risk of automation (Bonin et al., 2015). Thus, in light of the findings presented above, the analysis conducted by Arntz et al. (2016), suggests that the overall threat from advanced automation technologies is substantially lower compared to the one identified in studies based on an occupation-based approach (see e. g. Brzeski & Burk, 2015; Frey & Osborne, 2013). As already indicated above, this considerable difference is partly based on the fact that even in those occupations, to which Frey and Osborne (2013) attributed a high risk of automation, workers, at least to some degree, also carry out tasks that prove rather difficult to automate, such as work tasks encompassing face-to-face interaction (Arntz et al., 2016). Besides, the researchers argued that, even in the case when new technologies are, in fact, established within the workplace, workers may adapt to these changes by shifting towards other work tasks, thereby avoiding technological unemployment (Arntz et al., 2016). Based on their findings, the researchers concluded that it seems implausible that automation, and, in broader terms, digitalization will destroy a substantial number of jobs (Arntz et al., 2016).

Moreover, Arntz et al. (2016) also observed noteworthy cross-country differences. In this regard, Arntz et al. (2016) found that, for example, the proportion of automatable jobs in Korea amounts to a mere 6%, while the corresponding portion in Austria and Germany is substantially higher with about 12%. According to Arntz et al. (2016), such differences across countries may mirror overall dissimilarities in workplace organization, earlier investments in automation technologies, and disparities within workers' level of education. In terms of workplace organization, the authors found that, in general, countries that focus more heavily on communicative work tasks in their workplace organization possess a much smaller proportion of jobs at high risk of automation. With regard to previous technology investments, the researchers found that, in fact, the degree of automatability is substantially reduced in countries where investments in technology are already high (Arntz et al., 2016).

In line with the argument put forward by Arntz et al. (2016), who argued that it is essential to focus on individual tasks as opposed to entire occupations when seeking to determine the potential for automation (Arntz et al., 2016), Nedelkoska and Quintini (2018) equally aimed to account for the difference in task structures within occupations when estimating the proportion of jobs that are attributed a high risk of automation. It should be noted here that, while the researchers sought to determine the "current and potential disruption brought about by automation in the labor markets of OECD countries" (Nedelkoska & Quintini, 2018, p. 115), the authors did not specifically mention as to what time horizon their study referred to.
In view of the aforementioned points, the researchers found that "across the 32 countries, close to one in two jobs are likely to be significantly affected by automation, based on the task structures they involve" (Nedelkoska & Quintini, 2018, p. 7). More specifically, the researchers found that "the median job is estimated to have a 48% probability of being automated" (Nedelkoska & Quintini, 2018, p. 45). Further, in terms of the automation risk of distinct jobs, the analysis suggests that, based on current technological feasibility, around 14% of jobs in OECD countries exhibit an automation probability of over 70%, and thus, according to the probability categorization proposed by Frey and Osborne (2013), are highly automatable (Nedelkoska & Quintini, 2018). Similarly, Pouliakas (2018), while making use of data on heavily disaggregated job descriptions as well as data on the skill requirements of distinct jobs in order to establish determining factors of automation risk, found that about 14% of adult workers in the EU are bound to face considerable risk of being supplanted by automation technology. In other words, the findings suggest that around 14% of adult workers in the EU occupy jobs that belong to the high-risk category as proposed by Frey & Osborne (2013). As already mentioned above, jobs in the high-risk category contain a median automation probability greater than 70% (Frey & Osborne, 2013; Pouliakas, 2018). In view of their estimates, Nedelkoska & Quintini (2018) emphasized that, even though this relatively low number may not seem alarming at first, this number corresponds to about 66 million workers

in the 32 countries included in their study (Nedelkoska & Quintini, 2018). At the same time, the researchers noted that it is essential to acknowledge that the identified estimates solely refer to technological possibilities, thereby disregarding the pace of technology diffusion as well as the probability of adoption of new technologies (Nedelkoska & Quintini, 2018). As already illustrated above, the process of adoption, in particular, can be impacted by a number of different factors (Manyika et al., 2017; Nedelkoska & Quintini, 2018). Moreover, another finding from their study suggests that around 32% of jobs possess an automation risk in the range of between 50% and 70 % (Nedelkoska & Quintini, 2018). According to the authors, this finding highlights the possibility of considerable change in this group of jobs caused by automation in the manner of how the respective jobs are performed (Nedelkoska & Quintini, 2018). Put differently, according to Nedelkoska and Quintini (2018), it can be assumed that these jobs contain, on the one hand, numerous work tasks that can be automated, and which will therefore eventually vanish from the job description. On the other hand, these jobs also probably include several bottleneck tasks as presented by Frey and Osborne (2013), which prove to be more difficult to automate and thus, will likely increase in their salience (Nedelkoska & Quintini, 2018). In this regard, the authors reasoned that the automation of a certain number of work tasks will result in substantial changes concerning the skill requirements of the respective jobs (Nedelkoska & Quintini, 2018), a point that will be elaborated in more detail in the subsequent sections. Moreover, concerning the jobs located at the lower end of the automatability range, Nedelkoska & Quintini (2018) found that around 26% of jobs possess a probability of automation lower than 30%. Consequently, as concluded by Nedelkoska and Quintini (2018), when taking into account all of the numbers presented above, it can be argued that the findings in the study conducted by Nedelkoska and Quintini (2018) rather resemble the results determined by Arntz et al. (2016) as opposed to those reported by Frey and Osborne (2013). In addition, consistent with the findings by Arntz et al. (2016) the researchers identified significant discrepancy in automatability across countries. In general, the authors observed a considerably lower degree of automation potential among jobs in Anglo-Saxon, Netherlands, and Nordic countries compared to jobs in Germany, Chile, Japan, as well as Easter European and South European countries that all possess a significantly higher level concerning the risk of automatibility (Nedelkoska & Quintini, 2018).

2.2.5 Other Effects of Job Automation on Employment

As already indicated earlier, it is important to emphasize that the analysis of dominant studies in the context of job automation presented above only considers the substitution or displacement effect of automation, thereby neglecting other direct or indirect effects of automation that may compensate the labor-saving or job-destruction effect of automation (see e. g. Arntz et al., 2016; Bakhshi et al., 2017; Frey & Osborne, 2013; Vazquez et al., 2019). However, in order to obtain a more complete picture of the impact or effects of automation on the demand for labor it is important to acknowledge the existence of possible other effects that may potentially result from the adoption of modern automation technologies, and that may counteract the substitution or displacement effect of automation (see e. g. Acemoglu & Restrepo, 2018; Goos et al., 2019). In view of this, while not specifically investigating the so-called net-effect of automation in their analysis, Nedelkoska and Quintini (2018) maintained that, while technology will certainly displace specific jobs, it will also create new jobs. Thus, in light of the estimates presented above, it is, according to Arnold et al. (2018), important to note that in order to put forward any precise or specific predications regarding the effect of job automation on employment as a whole, it is essential to take into account not only the labor-saving or substitution effect of automation, but also its effects concerning job creation that may ultimately counteract or compensate the substitution or displacement effect (Arnold et al., 2018; Goos et al., 2019). In relation to this, a number of scholars (see e. g. Acemoglu & Restrepo, 2018; Goos et al., 2019; Vazquez et al., 2019) discussed different dynamics that promote the job creation effect of automation that may result from the adoption of new job automation technologies into the workplace.

To start with, the first effect underlying the job creation effect presents the productivity effect (Acemoglu & Restrepo, 2018; Vazquez et al., 2019). As pointed out by Servoz (2019), an important aspect to consider when seeking to anticipate the impact of modern job automation technologies on employment is to understand the effect of these technologies on productivity growth (Servoz, 2019). In this regard, the displacement of workers by sophisticated job automation technologies may effectuate a decline in production costs and prices, thereby raising demand and output, and, subsequently, increasing employment. In addition, modern technologies may enhance product quality or advance the development of new products and services, which, in turn, may potentially increase production and demand (Vazquez et al., 2019). Moreover, another effect that potentially could assist job creation presents the reinstatement effect (Acemoglu & Restrepo, 2018; Vazquez et al., 2019). In this context it is argued that technology may generate new work tasks as, first, while certain tasks are substituted by technology, workers may then use their time to perform new and potentially more productive work tasks, and second, the implementation of new machines or other automation technology may entail the development of and demand for entirely new tasks. As a result, this new task creation may directly compensate the displacement or substitution effect by increasing labor demand (Vazquez et al., 2019). Lastly, an additional effect of job automation that may potentially increase the demand for labor is the so-called capital accumulation effect where the implementation of modern automation technologies may effectuate increasing demand for new technology and machines, thereby raising the demand for work tasks that are knowledge-based as well as for tasks that encompass the production, implementation, and maintenance of newly adopted technologies (Acemoglu & Restrepo, 2018; Goos et al., 2019). Thus, whether the adoption of new automation technologies results in increased or decreased employment levels is ultimately dependent on the relative magnitude of the various effects discussed above (Goos et al., 2019). This being said, Vazquez et al. (2019) however noted that, while also emphasizing technology's potential of new job creation and development, it is a challenging and difficult task to anticipate what kind of jobs will be created.

2.2.6 Summary

As already argued in the beginning of this chapter, numerous forward-looking studies that aimed to quantify the so-called substitution effect of automation have been published in recent years due to the ongoing advances in automation and the associated potential threat of such progress in terms of overall employment levels across advanced economies (see e. g. Arntz et al., 2016; Frey & Osborne, 2013; Manyika et al., 2017; Nedelkoska & Quintini, 2018). In view of this, the foregoing discussion illustrates that, just as there is a significant variance in the potential impact of automation on countries and sectors, which, however, is not the focus of the present work and thus, will not be discussed further, estimates regarding the proportion of jobs that could be substantially affected by job automation, be it to a lesser or stronger degree, also vary widely (see e.g. Arntz et al., 2016; Frey & Osborne, 2013; Manyika et al., 2017; Manyika, Lund, Chui, et al., 2017). As shown throughout this chapter, this variation can be partly explained by the fact that researchers vary in their choice regarding the unit or level of analysis when seeking to assess the automation potential of a given job (see e. g. Arntz et al., 2016; Frey & Osborne, 2013). Thus, the varying quantifications and estimates obtained by the studies presented in the realm of this chapter can be, to a large extent, attributed to the methodology used in the respective studies (Patscha et al., 2017). In view of this, studies that followed an occupation-based approach (see e. g. Frey & Osborne, 2013) yielded substantially higher estimates in terms of the number of jobs at high risk of automation compared to studies that followed the so-called task-based approach (Arntz et al., 2016; Manyika et al., 2017; Patscha et al., 2017). While the occupation-based approach estimates the automation risk for whole occupations as opposed to the distinct tasks that a respective occupation encompasses, the task-based approach follows the assumption that it is the distinct work tasks instead of whole occupations that may be at risk of being automated (Patscha et al., 2017). In view of this, Frey and Osborne (2013), who were amongst the very first researchers that sought to determine the substitution effect of job automation on employment (Vazquez et al., 2019), as well as various other researchers followed a so-called occupation-based approach to assess the risk of automation, thereby following the assumption that occupations or jobs in their entirety rather than distinct work tasks are potentially automated by automation technologies (Arntz et al., 2016). However, as already stressed earlier, the high numbers of jobs at high risk of automation in the near future obtained through an occupation-based approach have recently been condemned due to the fact that they potentially overestimate the degree to which jobs as a whole could be automated in the near future (Cedefop, 2018). In view of this, various other researchers criticized this aggregated occupation-level approach proposed by Frey and Osborne (2013) by arguing that this approach significantly overestimates the potential of job automation as it disregards the heterogeneity of tasks across and within occupations, and because it does not account for the fact that workers may increasingly shift their focus on work tasks less susceptible to automation (Arnold et al., 2018; Arntz et al., 2016; Vazquez et al., 2019). Therefore, when seeking to assess the automation risk of jobs, it is essential to acknowledge the fact that workers, who belong to the same occupational category, may still carry out a differing set of tasks (Cedefop, 2018). All in all, as already indicated earlier in this section, the occupation-based approach may result in an overestimation concerning the potential of job automation, as those occupations, that were assigned a high risk of automation, could still comprise a considerable amount of work tasks that are difficult to automate (Arnold et al., 2018; Arntz et al., 2016).

In light of the arguments provided above, several researchers (see e. g. Arntz et al., 2016; Maynika et al., 2017; Pouliakas, 2018) argued for a task-based or, in general, a more disaggregated approach as opposed to the aggregated occupation-based approach followed by, for example, Frey and Osborne (2013) to assess the risk of automation for distinct jobs (Schlogl & Sumner, 2018). While the findings reported in the studies following a task-based approach suggest that in most jobs a certain amount of work tasks could potentially be automated, the findings also illustrate that, compared to the findings derived using an occupation-level approach, a much smaller proportion of jobs possess a high risk of automation (Arntz et al., 2016; Vazquez et al., 2019). As noted earlier, jobs that are allocated a high risk of automation refer to jobs in which at least 70% of associated tasks could be executed by modern automation technology (Frey & Osborne, 2013; Vazquez et al., 2019). Concerning this matter, the group of researchers, who based their estimates on the so-called occupation-based approach yielded, in general, significantly higher numbers than researchers, who made use of a much more disaggregated approach in their analyses (see e. g. Arntz et al., 2016; Frey & Osborne, 2013). In this regard, it becomes clear from the discussion above that analyzing the automation potential for jobs on the basis of the actual task structure of distinct jobs yields substantially lower estimates (Arnold et al., 2018). To illustrate, the proportion of jobs in the US that were allocated a high risk of automation decreases significantly from 47% with the assessment based on an occupational level approach, as conducted in Frey & Osborne (2013), to only 9% with the estimates based on a much more granular analysis as seen in Arntz et al. (2016) (Arnold et al., 2018). Consequently, estimates regarding the overall number of jobs at risk of automation vary significantly depending on the unit of analysis or the level of aggregation utilized in the different studies presented above (see e. g. Arntz et al., 2016; Frey & Osborne, 2013).

In sum, the arguments and insights presented in the present and previous chapter indicate that the overall impact of job automation on the number of jobs may be less severe than some researchers or other experts anticipate (Arntz et al., 2016; Dellot & Wallace-Stephens, 2017; Manyika et al., 2017). In view of this, the foregoing discussions presented throughout the previous as well as the present chapter provided a number of reasons that allow for a certain skepticism towards claims of automation-induced mass unemployment (Arntz et al., 2016; Dellot & Wallace-Stephens, 2017; Manyika et al., 2017). First, as mentioned in Chapter 2.1, several factors exist that act as potential barriers to automation and, thus, may significantly mitigate the actual extent or scope of automation (see e. g. Manyika et al., 2017). Second, the prevailing conception that jobs are made up of several tasks, which are not all automatable to the same extent, presents a further reason to believe that the actual extent of automation is expected to be less severe than propagated by some researchers or other experts (Arntz et al., 2016; Dellot & Wallace-Stephens, 2017). Third, the existence of other potential effects of job automation that may counteract the substitution effect of automation further mitigates claims about widespread unemployment brought about by automation (Acemoglu & Restrepo, 2018; Dellot & Wallace-Stephens, 2017; Vazquez et al., 2019). With regard to this, recent forecast studies that aimed to assess or quantify both the substitution or displacement effect caused by automation as well as the counteracting effects induced by automation including positive effects on overall demand, lower costs, and price reductions further alleviate rising concerns about widespread technological unemployment (Patscha et al., 2017). Thus, by taking into account not only the methodological aspect in terms of the unit of analysis analyzed in the different studies, but also the potential barriers to job automation discussed in the previous chapter as well as other potential effects of job automation that may compensate the job destruction effect of automation, wide-spread unemployment resulting from job automation seems highly unlikely to occur in the near future (Arntz et al., 2016; Manyika et al., 2017; Vazquez et al., 2019). However, even though there are many reasons to believe that job automation in the 21st century is not likely to significantly reduce the levels of employment, the findings presented above nevertheless indicate that the nature of work is changing (Maynika et al., 2017; Nedelkoska & Quintini, 2018; Tytler et al., 2019). With regard to this, even though the concrete scope and extent of job or task automation that may materialize in the decades ahead presents a key uncertainty, a common theme identified in the studies presented above is that they anticipate a future, in which automation in the workplace will be much more prevalent than today (Hajkowicz et al., 2016; Manyika et al., 2017; Nedelkoska & Quintini, 2018). In view of this, the analysis above nevertheless indicates that one can assume that job automation will still effectuate substantial changes in the very nature of a large amount of jobs as sophisticated automation technologies will increasingly be integrated into the workplace alongside human workers with the aim to yield the potential benefits that these technologies provide as discussed earlier in this work (Manyika et al., 2017; Nedelkoska & Quintini, 2018; Servoz, 2019; Vazquez et al., 2019). Thus, even though no one can predict for sure with a high degree of accuracy the net-effect of automation on employment, what seems to be certain, according to various researchers' assessments, is that the nature of work will undergo substantial changes (Arntz et al., 2016; Manyika et al., 2017; Nedelkoska & Quintini, 2018; Patscha et al., 2017; Servoz, 2019; Vazquez et al., 2019). With regard to this, Patscha et al. (2017) stressed that, while technological progress in the context of automation is unlikely to result in widescale technological unemployment across advanced economies, the work tasks within a wide range of occupations are expected to undergo significant changes, thereby changing the skill requirements of jobs impacted by automation (Patscha et al., 2017). This point will be further discussed shortly.

In view of the arguments and insights provided above, the subsequent section will build on these findings by looking, in more detail, at the distinct factors that determine the automation risk or so-called automatability of a given job. As the following discussion will illustrate, these insights entail important implications for predictions or forecasts in terms of future occupational trends and, in turn, anticipated shifts in future skill trends and demand within the context of increasingly automated work environments.

2.3 Determinants of a Job's Susceptibility to Automation

As already indicated above, the present section will elaborate on distinct factors that are recognized in the literature as important determinants for the automatability of a given job. However, while touching on a number of different determinants that are important to consider when seeking to estimate a job's automation risk, the discussion below, due to the limited scope of this thesis, will have its focus on the role or prevalence of distinct work tasks as essential determinants for the automatability of a job as already argued in the previous section due to their imminent importance for future occupational trends and, as a result, future skill requirements as will be argued throughout the subsequent sections and chapters (Arntz et al., 2016; Bughin et al., 2018; Lamb et al., 2018; Manyika et al., 2017; Patscha et al., 2017). As noted by Patscha et al. (2017), within the past few years, the concept of "tasks" has become a major focus topic in labor market research within the context of automation or, more specifically, automation potential. In view of this, Oschinski and Wyonch (2017), while pointing out that complex work tasks demand appropriately sophisticated skills that modern automation technology is currently not able to emulate, stressed that it may be valuable and useful to analyze the work tasks generally carried out by human workers and to differentiate these tasks based on their degree of susceptibility to automation. In this regard, as argued by the Foundation for Young Australians (FYA), specific information regarding future jobs and work activities in general is a prerequisite for determining the portfolio of the necessary skills demanded in order to thrive in increasingly automated workplaces (FYA, 2017). Underlining the argument put forward by the FYA (2017), Patscha et al. (2017) argued that "the tasks which make up occupations and job profiles form the basis for the skill requirements for labor demand" (Patscha et al., 2017, p. 29). While taking into account the aforementioned points, the subsequent discussion will outline the main factors that, based on the literature reviewed for the purpose of this chapter, constitute key determinants for the automatability of a given job as already mentioned earlier.

2.3.1 Job-Related Characteristics

In view of the aforementioned points, Manyika et al. (2017), who analyzed the technical automation potential for distinct work activities as elaborated above, classified the different types of work activities according to their degree of susceptibility to automation. In this regard, the authors found that certain kinds of activities including collecting or processing data, as well as carrying out physical activities and conducting machinery in a predictable environment exhibit a high technical automation potential. According to Manyika et al. (2017), these categories of work activities correspond to routine-type of work. In contrast, for some other work activities, the researchers identified a considerably lower susceptibility for automation including activities, such as interacting with stakeholders, deploying expertise to decision-making, creative tasks, planning, and managing and developing people, which, as noted by Chui et al. (2016), are often referred to as knowledge work. In addition, the authors' findings suggest a negative correlation between both an occupation's wage and skill requirements and its technical automation potential. Put differently, occupations that feature higher wages and skill requirements generally possess a smaller automation potential (Manyika et al., 2017). Based on these differing automation potentials for distinct work activities, Manyika et al. (2017) recognized a noteworthy variation in the degree of automation potential between and within sectors, as well as between the occupations inside these sectors. For instance, sectors that involve, to a large extent, predictable physical activities, such as manufacturing and retail trade, demonstrate a rather high technical automation potential, according to state-of-the-art technology. Thus, the technical automation potential between and within sectors differs according to the combination concerning the types of work activities (Manyika et al., 2017). While the aforementioned points are interesting to mention, it may be stressed at this point once again that, due to the limited scope of this thesis, the overall aim of the present thesis is to provide a thorough understanding of general future trends and changes in terms of jobs, tasks, and skills within the context of automation across advanced economies, rather than providing a sector-specific analysis of the subject matters at hand.

To continue, Arntz et al. (2016), who determined the job automation potential for jobs in 21 OECD countries, found that, overall, the automatability of jobs is considerably smaller in those jobs, which involve a high degree of educational job requirements, as well as in jobs that demand cooperation with others or where workers devote quite a substantial amount of their time in influencing others. In addition, the authors concluded that the automatability of jobs is significantly higher for those jobs that require a great share of tasks that are concerned with exchanging information, selling, or making use of fingers and hands (Arntz et al., 2016). These findings are consistent with the conclusions drawn by the so-called task-based literature (see e. g. Autor, 2014; Autor, 2015; Autor & Handel, 2013; & Autor et al., 2000 for a more detailed discussion), which suggests that so-called routine tasks are much more susceptible to automation as compared to interactive or cognitive tasks (Arntz et al., 2016; Autor, 2014; Autor, 2015; Autor & Handel, 2013; & Autor et al., 2000).

In relation to this, an important conclusion drawn by Nedelkoska and Quintini (2018) is that the risk of automation is not dispersed evenly among occupational groups. Regarding this issue, the researchers found that automation will mostly impact jobs in the manufacturing industry and agriculture, even though certain service sectors including postal and courier services, land transport, and food services also exhibit a high automation risk. In this context, the analysis suggests that those occupations, which possess the highest degree of automatability, usually only demand a basic to low educational level. In contrast, those occupations, which exhibit the lowest degree of automatability, typically demand a higher educational level, such as professional training or tertiary education and usually include a high number of tasks associated with social interaction, creativity, problem-solving, and caring for others (Nedelkoska & Quintini, 2018). It follows that those occupational groups that seem to be most at risk of being affected by automation, generally perform jobs that do not necessitate specific skills or training, including assemblers, laborers, and cleaners (Nedelkoska & Quintini, 2018).

Moreover, Muro et al. (2019), who conducted a forward-looking analysis of the impact of automation on employment and jobs in the US by 2030, found that work tasks related to collecting and processing information as well as physical activities along with conducting machinery in predictable physical environments all possess a high susceptibility to automation. As noted by Muro et al. (2019), such work tasks or activities are frequently found in occupations including office administration, construction, maintenance, as well as transportation and food preparation. Conversely, the researchers found that work tasks and activities, which entail a much lower susceptibility to automation include, but are not limited to, managing and developing people, applying expertise to decision-making, planning and creative tasks, along with carrying out physical activities and conducting machinery in unpredictable physical environments (Muro et al., 2019). As remarked by Muro et al. (2019), those work tasks and activities are typically found in management as well as professional and technical job roles and in job roles associated with personal care or interacting with others. With regard to these findings, the insights obtained entail important implications for the future automation potential of distinct occupations (Muro et al., 2019). In view of this, the researchers found that occupations within complex, creative, or social domains, such as management, science and technology, education, arts, and health care possess particularly low levels of automation potential (Muro et al., 2019). In contrast, as already indicated above, job roles including office administration, construction, maintenance, and food services possess notably high levels of automation potential (Muro et al., 2019).

Further, AlphaBeta (2017) also argued that automation potential differs between certain types of tasks. In view of this, AlphaBeta (2017) stressed that interpersonal tasks, tasks associated with information synthesis, as well as creative and decision-making tasks constitute, in general, tasks that are least likely to be automated. While interpersonal tasks primarily encompass the direct engagement with other people, creative and decision-making tasks usually require a high level of creative and out-of-the-box thinking (AlphaBeta, 2017). Lastly, information synthesis tasks typically include tasks associated with information interpretation as well as the extraction of meaning from simple data points (AlphaBeta, 2017). On the contrary, according to AlphaBeta (2017), tasks associated with information analysis along with predictable and unpredictable physical tasks usually possess a higher susceptibility to automation. Information analysis tasks typically encompass the gathering and processing of information, while predictable physical tasks generally involve repetitive and routine physical work (AlphaBeta, 2017). Finally, unpredictable physical tasks typically refer to tasks that cover a wider range of physical work that usually does not occur on a routine basis (AlphaBeta, 2017).

As already argued in the previous section, the risk of automation varies substantially across different jobs (see e. g. Nedelkoska & Quintini, 2018). In this regard, while the findings above imply that jobs that require higher levels of education and skill requirements possess a rather low automation potential, research also suggests that jobs most at risk of automation generally are characterized by displaying lower levels of education and skill requirements (Arntz et al., 2016; Manyika et al., 2017; Nedelkoska & Quintini, 2018). Thus, the level of educational requirements for jobs seems to be correlated with their probability of being automated (Manyika et al., 2017; Manyika, Lund, Chui, et al., 2017). This, in turn, indicates that workers occupying low-skill jobs are more at risk of experiencing job losses due to automation (Arntz et al., 2016; Servoz, 2019). As mentioned above, this points to an unequal distribution of the risk of automation among workers (Arntz et al., 2016; Manyika et al., 2017; Servoz, 2019). In this regard, Arntz et al. (2016), while coming to the conclusion that it seems rather implausible for automation to destroy a large number of jobs, emphasized, however, that workers, in general, will not experience automation equally. More specifically, the authors reasoned that it will be the low-qualified workers, who will be most affected by automation due to the substantially higher automation potential of their jobs compared the automation potential of jobs of high-qualified workers (Arntz et al., 2016). This unequal distribution concerning the job automation risk amongst workers suggests that job automation may potentially cause an increase in inequality, which, as will be discussed later in this work, demands appropriate policy measures and actions by different actors including organizations and education providers (Bughin et al., 2018; Servoz, 2019; WEF, 2018). In this regard, Arntz et al. (2016) argued that it is essential to put higher emphasis on the possible inequalities and necessities for training initiatives resulting from the implementation of job automation technologies into the workplace, rather than focusing on the overall threat of unemployment that these technologies may or may not cause (Arntz et al., 2016).

Moreover, in light of the arguments provided above, the findings derived from the literature further illustrate that the automation potential of a given job is predicated on the combination of work tasks that constitute a specific job (see e. g. Arntz et al., 2016; Manyika et al., 2017). For example, jobs or occupations that involve a high degree of tasks relating to social interaction or cooperation are much less susceptible to automation as opposed to jobs that contain a high degree of routine tasks and which do not require complex social interaction (Arntz et al., 2016; Manyika et al., 2017; Vazquez et al., 2019). This is in line with the argument put forward by Brynjolfsson and Mitchell (2017), who noted that the susceptibility of work tasks to automation is much higher when work is structured or organized in a highly discrete, standardized, and predictable manner (Brynjolfsson & Mitchell, 2017; Vazquez et al., 2019). Overall, the literature findings show that jobs that require to a large degree tasks, such as interactive and cognitive tasks, creative tasks, as well as tasks associated with managing and developing people are much less at risk of being affected by automation (see e. g. Arntz et al., 2016; Manyika et al., 2017). Conversely, the analysis also illustrates that jobs containing a large proportion of highly repetitive or rules-based tasks display a particularly high susceptibility to automation (see e. g. Manyika et al., 2017; Servoz, 2019). Overall, while "routine tasks can be captured in a rule or program, non-routine tasks are too variable and context-dependent to be standardized" (Lamb et al., 2018, p. 28). Accordingly, routine tasks entail a much higher automation susceptibility as opposed to non-routine work tasks (Lamb et al., 2018). It follows that, in general, the automation risk of a given occupation is, to a large degree, dependent on the amount of routine or non-routine work tasks that the respective occupation encompasses (Lamb et al., 2018). In view of the insights presented above, it becomes clear that the organization of work presents an essential aspect to consider when seeking to estimate the potential of job automation (Vazquez et al., 2019). In view of this, the discussion provided above shows that automation has the power to significantly change the nature of work tasks performed by human workers as stressed by AlphaBeta (2017). Overall, the studies presented throughout this chapter commonly agree that it is especially routine-based tasks with lower skill levels that possess a high risk of automation (Patscha et al., 2017).

2.3.2 Implications for Future Occupational Trends, Work Tasks Structures, and Skill Requirements of Jobs

This being said, the findings in terms of the task content of a job being an important predictor of the respective job's automation risk presented in this section have important implications for future occupational trends and their associated task structures (see e. g. Bughin et al., 2018; Cedefop, 2018). In this regard, in spite of the fact that one can assume that changes in employment levels potentially brought about by job automation will not be significant, a number of researchers and scholars still anticipate substantial structural changes across and within occupations (Acemoglu & Restrepo, 2018; Arnold et al., 2018; Bughin et al., 2018; Cedefop, 2018; Manyika, Lund, Chui et al., 2017; Pouliakas, 2016). Acemoglu and Restrepo (2018), for example, argued that, while it is anticipated that the aggregate net employment effect as a result of automation will stay rather small, it is still expected that the wide-scale adoption of modern automation technologies will effectuate strong occupational restructuring that may result in workers facing the need to shift from rather routine towards non-routine occupations (Acemoglu & Restrepo, 2018). In addition, Pouliakas (2016) stressed that, even though certain jobs may not be entirely displaced by job automation technology, they still entail a high likelihood of experiencing substantial changes in their task content (Pouliakas, 2016). In this context, Manyika, Lund, Chui et al. (2017) argued that, for the majority of occupations, automation will considerably transform the range of activities that are carried out by human workers as certain work tasks will increasingly be executed by modern automation technology. In relation to the aforementioned points, Shook and Knickrehm (2018) stressed that merely concentrating on job decline or job growth as potential effects of job automation neglects a critical point in the sense that the strongest effect of modern automation technologies, such as artificial intelligence, concerns the impact on the job content. As found by the authors, classical job descriptions are becoming increasingly outdated as automation performs routine tasks, while human workers shift towards other work tasks, such as project-based work (Shook & Knickrehm, 2018). The different effects of job automation will be discussed in more depth in the next chapter.

In view of the arguments provided above, Manyika, Lund, Chui et al. (2017) found that, in the future, workers are expected to perform to a stronger degree those activities, for which modern automation technology does not have sufficient capacity or capabilities to perform them adequately, such as managing people, applying expertise, and communicating with others. This prediction is consistent with the findings presented earlier in this chapter, which illustrated that tasks that are related to managing and developing people, applying expertise to decision-making, as well as communication are less susceptible to automation and hence, are at lower risk of being automated (see e. g. Arntz et al., 2016; Manyika et al., 2017; Pouliakas, 2018). At the same time, Manyika, Lund, Chui et al. (2017) found that, in the future, workers are anticipated to spend reduced time on work activities, in which automation technology already surpasses the performance of human workers, such as predictable physical activities along with collecting and processing data. This forecast seems to be, again, in accordance with the findings presented earlier, which illustrated that work activities associated with collecting or processing data as well as carrying out physical activities in predictable environments are much more at risk of being automated due to their high susceptibility to automation (see e. g. Arntz et al., 2016; Manyika et al., 2017). In relation to the aforementioned points, Hajkowicz et al. (2016) noted that, as work tasks that require to a large extent creativity, complex judgement, advanced reasoning, social interaction, as well as emotional intelligence are and continue to be, at least in the near future, out of reach for even highly sophisticated automation technologies, jobs that are largely predicated on such tasks are expected to grow in demand throughout the decades to come. At the same time, jobs that encompass to a large extent repetitive, rules-based, structured, and routine tasks that are highly susceptible to automation will likely diminish in numbers (Hajkowicz et al., 2016).

Moreover, similar to the findings obtained by Arnold et al. (2018), who found that, in general, future jobs are likely to involve more mentally demanding requirements and fewer physically demanding work tasks, the insights of the study conducted by the FYA (2017) suggest that, as the implementation of modern automation technologies into the workplace lessens the need for workers to carry out routine, manual work tasks, it is expected that workers will devote much more of their time to work tasks associated with people, resolving more strategic problems in addition to creative thinking (FYA, 2017). More specifically, the findings obtained by the FYA (2017) suggest that, in the future, workers will, in general, spend more of their working time on establishing and sustaining relationships with their co-workers or clients, interacting with other people, as well as on tasks related to complex reasoning, decision-making, and creativity (FYA, 2017). Similar to the study insights obtained by the FYA (2017), the findings acquired by AlphaBeta (2017), who conducted an analysis in terms of how automation is shifting the time duration spent on distinct work tasks by the year 2030 in Australia, suggest that the average Australian worker is expected to devote two hours per week less on highly automatable manual and routine tasks including tasks associated with information analysis as well as unpredictable and predictable physical tasks (AlphaBeta, 2017). Accordingly, the results imply that workers will spend two additional hours per week on tasks less susceptible to automation including interpersonal tasks, information synthesis tasks, as well as creative and decision-making tasks (AlphaBeta, 2017). In relation to the aforementioned points, the WEF (2020) argued that, within the context of increasingly automated future work environments, modern automation technologies including artificial intelligence and robotics will predominantly carry out tasks, such as traditional manual work, information and data processing and retrieval, as well as administrative tasks, while human workers will particularly focus on tasks for which they hold a comparative advantage including tasks related to managing, advising, decision-making, reasoning, communicating, as well as interacting (WEF, 2020).

Overall, these insights outlined above regarding the forecasts of future trends of jobs and work tasks increasingly performed by human workers entail, in turn, important implications for the future skills required to succeed in workplaces of the future as will be outlined in the following and discussed in more detail throughout the next chapter (FYA, 2017; Oschinski & Wyonch, 2017).

In view of this, the findings established by Manyika, Lund, Chui et al. (2017), who analyzed potential future job growth and decline across 46 countries by 2030, suggest that, in advanced economies, those occupations that are likely to grow entail higher educational requirements compared to those occupations that are expected to decline due to automation. In addition, the findings further indicate that, while many routine-based work tasks will be taken over by automation technology, the work activities performed by human workers will increasingly shift towards tasks requiring human interaction, application of expertise, and working in unpredictable environments. Consistent with these findings, the ILO (2018) argued that, as jobs that include high levels of routine tasks are becoming increasingly automated, workers will be more and more shifting to jobs that involve a large extent of non-routine work tasks that typically demand advanced cognitive as well as social and emotional skills (ILO, 2018). Thus, the shifts in work tasks, in turn, will implicate substantial changes in the skills needed to succeed in the future labor market as will be thoroughly discussed in the next chapter (Manyika, Lund, Chui et al., 2017). As argued by Lamb et al. (2018), even though automation is not expected to obliterate employment, it is, nevertheless, shaping and altering both the nature of work as well as the skills required. In view of this, as stressed by Patscha et al. (2017), "the tasks which make up occupations and job profiles form the basis for the skill requirements for labor demand" (Patscha et al., 2017, p. 29). Overall, by seeking to foresee how work tasks within occupations are likely to change, this provides some indication regarding the kind of skills that, in the years to come, are expected to be more or less in demand (Manyika, Lund, Chui et al., 2017). In this context, the researchers also argued that, in particular in advanced economies, these changes in work tasks and the associated skill requirements will affect the majority of jobs, even though to potentially differing degrees (Manyika, Lund, Chui et al., 2017). With regard to the anticipation of future skills demand, Cedefop (2018) argued that predictions concerning future employment trends also entail significant implications for future skill trends. In this context, Cedefop (2018) remarked that assessments regarding future structural changes across and within occupations allow for making reasonable deductions in terms of the work tasks and skills that are expected to become increasingly relevant in the years to come (Cedefop, 2018).

As argued by Arnold et al. (2018), this anticipated resulting structural change due to job automation discussed above will effectuate some substantial alterations in the qualification and skill requirements of jobs. This is in line with the argument put forward by Neuberger-Fernandez and Barton (2017), who maintained that technologies including artificial intelligence and robotics are changing the nature of work and the skills required to succeed. Consistent with this, Bughin et al. (2018), who conducted a survey in March 2018 with around 3,000 C-level executives from companies in the US and Europe, found that, while approximately 77 percent of survey respondents reported that they do not anticipate a net change in workforce size due to the adoption and implementation of automation within the next few years, they did, however, argue that the composition of jobs and skills will undergo substantial changes (Bughin et al., 2018). In relation to the aforementioned points, Goos et al. (2019) emphasized that the potential job-creation and job-destruction effects of automation imply a great shift in the skill demands of future jobs, and that the adoption and implementation of modern automation technologies into the workplace are anticipated to effectuate substantial changes in the task content of jobs, which, in turn, is expected to result in significant changes in the skill requirements of jobs (Goos et al., 2019).

To conclude, the points outlined above illustrate that, along with the education requirements of a given job, the skill requirements as well as the task structure of a given job constitute strong determinants of the automation potential of the respective job (see e. g. Arnold et al., 2018; Bughin et al., 2018; Goos et al., 2019). These findings are essential as they have, as demonstrated above, strong implications for future occupational trends and their associated job characteristics including their task structures along with their skill requirements (see e. g. Bughin et al., 2018; Cedefop, 2018; FYA, 2017; Lamb et al., 2018; Patscha et al., 2017; Pouliakas, 2016). With regard to the aforementioned points, it is, however, important to stress at this point that, despite the fact that, besides skill requirements, education requirements that commonly encompass educational qualifications including high school diploma, college diploma, or bachelor degree (see e.g. Lamb et al., 2018) play an important role with regard to the future of work in the context of automation as illustrated earlier, the present thesis along with its central research question nevertheless seek to exclusively understand and investigate the anticipated changes in the so-called skill requirements of jobs as a result of increasingly automated work environments. Hence, while acknowledging the importance of addressing the topic of educational requirements when aiming to discuss the topic of automation in the context of future work and jobs, it is essential to emphasize that, for the purpose of both highlighting the central concern of this thesis and focusing on answering the central research question of the present work, the remainder of this thesis will focus exclusively on the requirements of a given job that relate to the concept of skills. This being said, the above-outlined forecasts and predictions in terms of future occupational trends along with the corresponding skill requirements and task structures entail, in turn, important implications for general future skill trends and thereby the overall skill requirements of future jobs (Bughin et al., 2018; Cedefop, 2018; FYA, 2017; Lamb et al., 2018; Patscha et al., 2017; Pouliakas, 2016). As stressed by Goos et al. (2019), developing an understanding about anticipated changes in the skill requirements of jobs in the context of automation is essential in order to be able to adequately respond to those anticipated changes with appropriate measures and policies, thereby closing potential skill gaps and strengthening worker employability (Goos et al., 2019). The potential contribution of advancing the overall understanding of general future skill trends was already thoroughly discussed in the beginning of this work.

In view of the issues and points outlined above, the subsequent chapter builds on the findings and insights elaborated throughout the present chapter by discussing important implications of the findings highlighted in this chapter in terms of the anticipated changes in the occupational structure in labor markets as well as of expected future trends of the task structures of jobs for future skill trends and skill requirements of jobs and thereby directly addresses the central research question the present thesis seeks to answer.

2.4 The Effects of Automation on Jobs & Anticipated Future Skill Trends and Demand

As already indicated above, the present chapter will extend the findings and insights presented and discussed in the previous chapter by elaborating in detail the different effects of automation on jobs along with their implications for future skill requirements of jobs, as well as by thoroughly presenting the anticipated future skill trends and changes in the skill requirements of jobs that are expected to unfold or emerge within the context of increasingly automated work environments as identified by extant literature.

2.4.1 Job Destruction, Job Creation, and Job Transformation: The Effects of Automation on Jobs and their Implications for Skill Requirements of Jobs

The previous chapter already discussed, to a certain extent, the different ways in which job automation may potentially impact jobs within the next few years across advanced economies. Based on this, as already argued earlier, the present chapter builds on these findings by elaborating in more detail the various effects of automation on jobs and based on this, will infer important implications for the skill requirements of future jobs. As remarked by Cedefop (2017), before seeking to draw inferences about future developments, such as changing skill requirements of jobs, it is essential to thoroughly understand the various ways, in which sophisticated automation technologies are impacting jobs including the substitution or destruction, creation, and transformation of jobs (Cedefop, 2017; Manyika et al., 2017; Manyika, Lund, Chui et al., 2017; Nedelkoska & Quintini, 2018; Vazquez et al., 2019; WEF, 2018).

Before discussing the aspects cited above in more detail, the following discussion will first focus on the meaning of skills and the definition of a *skill* that is used for the purpose of the present thesis. As argued by the Business Council of Australia (2016), within the context of the workplace, the concept of *skills* constitutes one of three factors that, together with the other two concepts of values and behaviors, make up the so-called "work readiness" mixture, and thus presents an essential factor that employers are looking for within potential employees (Business Council of Australia, 2016). Further, according to various sources (see e. g. Lowry et al., 2008; OECD, 2013; Payton & Knight, 2018), the notion of a *skill* presents a concept that seems elusive and hard to define. Accordingly, a variety of definitions exist in the literature in order to refer to the concept of a *skill* (see e. g. Bughin et al., 2018; Cunningham & Villaseñor, 2014; Delisle, 2019; OECD, 2013; Oschinski & Wyonch, 2017). With regard to this, Bughin et al. (2018), for example, remarked that the academic literature employs different definitions when seeking to reference the notion of *skills* (see e. g. Bughin et al., 2018 for further details). Delisle (2019), for example, refers to *skills* as "developed capacities that an individual must demonstrate to be effective in a job, role, function, task, or duty" (Delisle, 2019, p. 18), while Cunningham and Villaseñor (2014) argued that, in short, the notion of *skills* can generally be defined as "the capacity to perform a specific task" (Cunningham & Villaseñor, 2014, p. 5).

In view of this, for the purpose of defining the concept of a *skill*, this thesis adopts the definition initially proposed by the OECD (2011), who referred to the concept of *skills* as "the bundle of knowledge, attributes and capacities that enables an individual to successfully and consistently perform an activity or task, whether broadly or narrowly conceived, and can be built upon and extended through learning" (OECD, 2011, p. 7). With regard to defining the notion of *skill*, Oschinski & Wyonch (2017), who defined a *skill* as "an ability, whether learned or inherent, that facilitates the learning, acquisition and application of knowledge" (Oschinski & Wyonch, 2017, p. 3), noted that, while some skills demand learned procedures, other skills are more abstract (Oschinski & Wyonch, 2017). Further, Oschinski and Wyonch (2017) pointed out in this context that the types of skills that one is able to obtain by means of learned procedure are much more susceptible to automation. Moreover, the present thesis follows the approach put forward by Bughin et al. (2018), who, in order to comprehend both the nature as well as magnitude of the anticipated shifts in skill demand, integrated both intrinsic abilities, such as gross motor skills and strength, creativity, and empathy, as well as specific learned skills including skills related to IT (Information Technology) and programming along with technology design, into their definition of *skills*. According to Bughin et al. (2018), this approach to define skills enables the development of a holistic depiction of the evolving nature of workforce skills, while, at the same time, ensuring an adequate level of detail to incite specific and appropriate action measures, of which some will be discussed later in this work. Further, in view of the points cited above, the Organization for Economic Co-operation and Development (OECD, 2013) pointed out that, within the literature, the notion of a *skill* is at times distinguished from the notion of *competency*. As remarked by the OECD (2013), *competency* is often referred to as a capacity that can be utilized throughout a wide range of different contexts, while a *skill* "is considered a constituent unit of competency, that is, a specific capacity, often technical in nature, relevant to a specific context" (OECD, 2013, p. 19). However, with regard to this, the OECD (2013) stressed that, while emphasizing that throughout their work no distinction is being made between the notions of *skill* and *competency*, a *skill* or *competency* can be referred to as "the ability or capacity of an agent to act appropriately in a given situation" (OECD, 2013, p. 19). Further, the OECD (2013) argued that both concepts "involve the application of knowledge (explicit and/or tacit), the use of tools, cognitive and practical strategies and routines, and both imply beliefs, dispositions and values (e. g. attitudes)" (OECD, 2013, p. 19). In light of this, the present work will follow the example put forward by the OECD (2011, 2013) by emphasizing that, for the purpose of the present thesis, no distinction is made between the notions of *competency* and *skill* and thus, the two notions are used interchangeably throughout this work.

This being said, the following discussion will now focus on the varying effects of automation on jobs along with their implications for the skill requirements of future jobs as already mentioned in the beginning of this chapter.

Job destruction & job decline

To start with, as already discussed earlier, sophisticated automation technologies could potentially displace entire jobs as reported by, for example, Manyika et al. (2017), who found that a certain number of jobs in the global economy, albeit only a rather small amount, could be automated completely. In relation to this, Manyika, Lund, Chui, et al. (2017) found that globally, by 2030, between 400 million and 800 million individuals could potentially be displaced by automation and thus, are required to find new jobs. In view of this, the researchers' findings illustrate that a substantial share of the total amount of individuals potentially displaced could be required to shift to different job categories, which, in turn, according to the researchers, necessitates the acquiring and developing of new skills (Manyika, Lund, Chui, et al., 2017). Consistent with this, Manyika & Sneader (2018) argued that, as a number of occupations are expected to decline in the coming years due to automation, some workers will be required to shift from declining towards growing or even entirely newly emerging occupations, which, in turn, will, in general, entail the necessity for those workers to obtain new skills. In this context, the findings also imply that, within advanced economies, such as the United States (US), Germany, and Japan, the proportion of individuals required to shift to new jobs and obtain new skills is particularly high (Manyika, Lund, Chui, et al., 2017). In this context, a number of scholars pointed out that the skill requirements that the new jobs entail are often substantially different to the skill demands in the job roles that were lost due to automation (Manyika, Lund, Chui, et al., 2017; Servoz, 2019; WEF, 2018). With regard to this, Hajkowicz et al. (2016) argued that the increasing employment and utilization of modern automation technologies within workplaces effectuate an increase in the complexity of work tasks performed by human workers, which, in turn, results in higher skill requirements of jobs. Moreover, while certain occupations may not be entirely disappearing, they may still experience a substantial decline in demand as reported by various researchers (see e. g. Manyika, Lund, Chui, et al., 2017; WEF, 2018). In this context, a survey concerning the future of work conducted by the WEF (2018), for example, showed that jobs that are anticipated to decline in relevance and numbers in the near future encompass jobs encompassing mainly routine type of tasks and which do not require particular high levels of skills including secretaries, auditors, as well as bank tellers and cashiers as those constitute job roles that possess a relatively high susceptibility to automation (WEF, 2018). Moreover, Manyika, Lund, Chui, et al. (2017) found that, in advanced economies, jobs that are most at risk of being automated and thus, will likely see a decline in the future encompass office support occupations including office assistants and finance and accounting work, as well as certain customer interaction jobs, such as cashiers and food service workers, along with a substantial number of jobs that are performed in predictable environments including food preparation workers and drivers.

In light of the arguments provided above, Manyika, Lund, Chui, et al. (2017) emphasized that both the labor displacement due to automation as well as the shifts in demand for occupations are expected to entail considerable implications for workers. While it is anticipated that a substantial number of workers will be required to switch to new occupational categories, the majority of jobs will experience significant shifts in their work tasks and activities (Manyika, Lund, Chui, et al., 2017). In this sense, Manyika, Lund, Chui, et al. (2017) argued that, while a larger share of jobs in the future are likely to demand greater levels of educational attainment, the skills required are also expected to undergo substantial transformations. For example, skills related to personal interactions as well as high levels of cognitive skills are expected to become increasingly important (Manyika, Lund, Chui, et al., 2017). This point will be further discussed in the subsequent section, which, as already argued earlier, will provide a more detailed analysis of future skill trend, changes, and demand.

Job creation & job growth

In addition, while technology has the potential to displace entire jobs, it may also promote the growth of existing jobs as well as create entirely new jobs (Vazquez et al., 2019; Manyika et al., 2017; Manyika, Lund, Chui, et al., 2017; Nedelkoska & Quintini, 2018; WEF, 2018; WEF, 2020). With regard to this, the WEF (2020), for example, estimated that, while, by 2025, the adoption and implementation of automation within the context of the 26 economies included in their study is expected to result in the displacement of 85 million jobs due to a novel division of labor between automation technology and human workers, it is also anticipated that this new division of labor results in the emergence of 97 million new job roles (WEF, 2020). However, as already argued earlier, it is a challenging task to precisely predict what kind of jobs will be created (Vazquez et al., 2019). In this regard, Manyika, Lund, Chui, et al. (2017) pointed out that, in the same manner that numerous occupations that exist today including app or website designer could not have been confidently predicted within the pre-internet era, it presents a difficult or even impossible endeavor to make reliable forecasts about the potential new occupations that may emerge in the near future. Nevertheless, although it may not be possible to precisely foresee which new jobs will arise in the years to come, certain jobs or occupations are assumed to entail a high probability to emerge or to develop in the future (Servoz, 2019). For instance, due to the growing adoption of artificial intelligence technologies, there seems to be a high likelihood that there will be an increase in demand for data scientists (Servoz, 2019). A data scientist refers to "a professional responsible for collecting, analyzing, and interpreting large amounts of data so as to identify ways to help a business improve operations and gain a competitive edge over rivals" (Servoz, 2019, p. 47). Further, the advancement of sophisticated technologies, such as artificial intelligence, brings up various ethical issues, which, in turn, may entail a growth in demand for ethics officers, who are in charge of monitoring different aspects of organizational practices or processes in order to ensure that they are in accordance with the organization's codes of ethics (Servoz, 2019).

Moreover, in relation to this aspect of new job creation due to the increasing adoption and implementation of automation technologies into the work environment, the analysis concerning the future of work in the near future conducted by the WEF (2018) suggests that a group of appearing job roles will likely considerably increase in relevance and significance in the next few years to come, while a different set of job profiles is expected to become progressively redundant (WEF, 2018). In this regard, employers questioned in the context of the research study carried out by the WEF (2018) anticipate that by the year 2022, the structural decrease of specific jobs, which is expected to amount to 10%, will be completely offset by the growth of novel job roles and professions, which is anticipated to comprise 11% (WEF, 2018). For instance, survey respondents anticipated the emergence of new job roles in the domain of project-based, temporary and freelancing work (WEF, 2018). In addition, entirely new job roles associated with comprehending and exploiting modern technologies, such as artificial intelligence and machine learning specialists, big data specialists, process automation experts, robotics engineers together with human-machine interaction designers are also expected to emerge and accelerate in demand (WEF, 2018). In addition, the findings suggest that established job roles, which are considerably predicated on and amplified by the utilization of new technology, are also anticipated to grow in demand including data scientists and analysts, software and applications developers, as well as e-commerce and social media specialists (WEF, 2018). In addition, similar to the findings obtained by the survey conducted by the World Economic Forum (WEF) in 2018 (see WEF, 2018), the findings yielded by means of the recently conducted 2020 survey that are presented in the new report about the future of jobs in the context of increasing automation published in October 2020 by the World Economic Forum suggest a clear pattern of development and trends with regard to newly emerging job roles as a result of the adoption and implementation of automation technology (WEF, 2020). More specifically, the survey results suggest that, by 2025, the job roles that are expected to emerge or increase in demand not only include data analysts and scientists, artificial intelligence and machine learning specialists, robotics engineers, along with software and applications developers and digital transformation specialists, but also job roles, such as process automation specialists, information security analysts, as well as Internet of Things specialists (WEF, 2020). As stressed by the WEF (2020), these anticipated trends regarding newly emerging job roles in the context of increasingly automated work environments clearly illustrate the accelerating pace of automation together with the emergence of cybersecurity risks (WEF, 2020). Moreover, as found by the WEF (2018), job roles that leverage inherently human skills, such as customer service workers, sales and marketing professionals, organizational development specialists along with innovation managers are also anticipated to grow (WEF, 2018). In relation to this, the findings suggest that human resource specialists, as well as sales and marketing professionals and specialized sales representatives are also likely to increase in demand in the near future (WEF, 2018). In view of the arguments provided above, while the findings imply that, in general, job displacements will be compensated by new job growth, the analysis also indicates that there will be a substantial change in the nature of job roles including the quality and format of new emerging roles (WEF, 2018).

Moreover, in their analysis covering 46 countries, Manyika, Lund, Chui, et al. (2017), sought to assess the number and types of jobs that may be created due to modern job automation technologies by 2030 and compared them to the types of jobs that could potentially be displaced by automation within this time horizon. In this regard, the researchers found that, across all countries, the job categories displaying the highest percentage of job growth comprise health-care providers, professionals such as engineers, scientists, accountants, and analysts, as well as IT (Information Technology) professionals and other technology specialists in addition to manual and service jobs in unpredictable environments along with managers and executives, whose work can also not easily be displaced by sophisticated automation technology (Manyika, Lund, Chui, et al., 2017). In this regard, the researchers pointed out that workers in these occupational groups cited above spend a significant amount of time on work activities that are characterized by a low susceptibility to automation as already identified in the previous chapter as they demand inherently human capabilities and thus, prove difficult for automation technology to perform including social and emotional interaction, higher-level logical reasoning, creativity, and application of expertise (Manyika, Lund, Chui, et al., 2017). Moreover, the researchers argued that jobs in the future are also expected to demand greater levels of performance in terms of many required skills (Manyika, Lund, Chui et al., 2017). In this regard, while automation technology may have the capacity to, for example, execute work activities demanding basic levels of skills associated with acquiring information and comprehending natural language, jobs that demand higher levels of these skills will likely grow in demand (Manyika, Lund, Chui et al., 2017). In relation to this, Servoz (2019) pointed out that certain jobs may increase in quantity and importance due to the fact that they may be very difficult to automate as they require skills that are, by their very nature, human. Such skills encompass, among others, social intelligence, which refers to the capacity to "negotiate complex social relationships" (Servoz, 2019, p. 45), cognitive intelligence, which includes "creativity and complex reasoning in an artistic context" (Servoz, 2019, p. 45), as well as perception or manipulation, which refers to "the ability to carry out tasks in an unstructured or unpredictable environment (Servoz, 2019, p. 46).

With regard to these insights, the dynamics discussed above concerning job automation's potential for new job creation and job growth have important implications for future skills demand (Manyika, Lund, Chui, et al., 2017; Servoz, 2019; WEF, 2018). In view of this, Manyika, Lund, Chui, et al. (2017) emphasized that the anticipated changes in job decline and job growth imply that a large share of individuals are potentially required to shift to new job categories, which, in turn, results in the necessity to acquire and develop new skills. In this regard, Servoz (2019) pointed out that, in general, future new jobs will entail substantially higher levels of skills. Relating to this aspect, while acknowledging the prospect of a substantial change in skill needs as a result of newly emerging job roles, the World Economic Forum (WEF, 2018) emphasized the need to develop a workforce adequately equipped with the necessary skills through reskilling and upskilling initiatives in order to fully seize the newly emerging job creation possibilities as well as to prevent a decline in the company's competitive capacity due to the workforce's skills obsolescence (WEF, 2018). This crucial point concerning appropriate reskilling and upskilling measures will be further explored in Chapter 4.2.1.

Job transformation & augmentation

Further, as demonstrated in the previous chapter and according to various researchers and scholars, it is mostly distinct tasks as opposed to whole occupations that are affected by automation (see e. g. Arntz et al., 2016; Vazquez et al., 2019; WEF, 2018). Thus, even though automation entails the potential to eliminate entire jobs as discussed earlier, in many cases it rather takes place at the task-level, thereby considerably changing and transforming the respective job instead of eradicating the job in its entirety (McKay et al., 2019). In this regard, as discussed in the previous chapter, Manyika et al. (2017) for example found that, in the case of the US, only five percent of entire occupations are at risk of being fully automated, while nearly 60% of all occupations encompass at least 30% of work activities that could be executed by automation technology. Consequently, technologies do not merely eliminate or create jobs, but they have the potential to substantially transform existing jobs, thereby altering or modifying what workers do as part of their jobs and the way they perform their jobs (Vazquez et al., 2019). In this regard, as discussed earlier, Nedelkoska & Quintini (2018), for example, found that around 32% of jobs across OECD countries possess a probability of automation in the range of between 50% and 70 %. Thus, while those jobs may not be entirely automated, a certain proportion of work tasks that constitute these jobs may still be automated (Vazquez et al., 2019). As argued by Bisello et al. (2019) and McKay et al. (2019), this may result in substantial changes in the task content of jobs. With regard to this, McKay et al. (2019) noted that, as any given job involves a variety of distinct work tasks, of which some may become automated, human workers will need to shift their work focus on carrying out other, differing work tasks. Consequently, as noted by Vazquez et al. (2019), job profiles may undergo significant changes as new work tasks are added or as existing work tasks are adjusted and modified. This, in turn, necessitates that workers are required to adjust and conform to different working methods or a new kind of work organization (Vazquez et al., 2019).

Further, concerning the transformation of jobs due to job automation, Servoz (2019) pointed out that, while the respective automation technologies may automate specific tasks in a given job, this then enables the workers to shift their focus on potentially more qualitative work tasks. Thus, in these cases, sophisticated automation technologies, such as artificial intelligence, are augmenting rather than displacing human workers in their respective jobs (Servoz, 2019). Consistent with this, while a number of forecast studies suggest that advanced automation technology will cause widespread displacement of workers from their jobs as discussed in the previous chapter, the findings obtained in the realm of a near-future analysis concerning the future of work conducted by the WEF (2018) imply that, rather, sophisticated automation technology augments the work or work tasks currently carried out by human workers (WEF, 2018). As argued by Manyika and Sneader (2018), "partial automation will become more prevalent as machines complement human labor" (Manyika & Sneader, 2018, p. 3). In view of this, the authors noted that the ability of artificial intelligence algorithms to interpret diagnostic scans with a high level of precision and accuracy is assisting doctors in making diagnoses and in determining adequate treatment options (Manyika & Sneader, 2018). In this sense, the responses collected by means of the study project conducted by the WEF (2018) imply that employers are increasingly focused on implementing a so-called augmentation strategy (WEF, 2018). This means that companies can make use of the automation of certain work tasks to improve and complement the capacities of human workers and, thus, to allow and support workers to utilize their inherently human talents and eventually to reach their full potential by freeing them from executing highly routinized and repetitive work tasks (Davenport & Kirby, 2015; Ton & Kalloch, 2017; WEF, 2018). In this regard, the findings obtained in the realm of a near-future analysis concerning the future of work conducted by the WEF (2018), for example, suggest that the augmentation of jobs by the means of technology may displace workers from tasks including data processing and information inquiry while, at the same time, allowing them to focus on much more valuable work tasks including reasoning and decision-making (WEF, 2018). Relating to this, Manyika et al. (2017), for example, noted that automation will provide an opportunity for workers to harness the inherent human skills that hitherto established machines find most difficult to emulate adequately, including social and emotional capabilities, offering expertise, creativity, and coaching and developing others (Manyika et al., 2017). Today's work conditions often require human workers to perform routine tasks, which, however, do not challenge these workers in exactly those innate capabilities cited above. Hence, as automation technologies and machines will increasingly perform predictable and routine work activities, the inherent human skills will become ever more important. Thus, in the words of Manyika et al. (2017), "automation could make us all more human" (Manyika et al., 2017, p. 115). This point is also underlined by AlphaBeta (2017) by stressing that, as automation is increasingly performing the most dangerous, most tedious, as well as least valuable tasks, thereby increasing the safety, meaning, and value of work, "human work will become more human" (AlphaBeta, 2017, p. 8). In addition, McKay et al. (2019) stressed that, within the near future, human workers will continue to hold a competitive advantage over automation technologies in performing non-routine tasks, which, ultimately, causes future jobs to become more "human" (McKay et al., 2019).

Further, in relation to the aforementioned points, Shook and Knickrehm (2018) argued that modern automation technologies, such as artificial intelligence, can assist businesses to move above mere automation through advancing or enhancing human capacities that promote new value creation. As stressed by the authors, the great potential of sophisticated automation technologies including artificial intelligence lies in the collaboration of both humans and machines that can yield high-value outcomes, such as increased customer experiences, as well as the creation of novel products, services, and markets (Shook & Knickrehm, 2018). Thus, advanced automation technologies constitute useful means to complement and enhance human labor (WEF, 2018). Consequently, advanced automation technology could allow workers to be freed from performing repetitive work tasks and empower workers to focus more heavily on performing more complex and higher-value work tasks and thus, has the potential to significantly augment human workers and increase productivity (Brown et al., 2017; WEF, 2018). Hence, while such sophisticated automation technologies may displace workers from specific tasks, in effect, they are able to greatly enhance and augment the workers' abilities (Dellot, 2018; WEF, 2018). In this context, Oschinski & Wyonch (2017), while pointing out that the effect of automation on the labor market is to a large extent based on whether the respective technology acts as either a substitute or a complement to human labor, argued that complex work tasks, which generally possess a rather low potential for automation (Arntz et al., 2016; Manyika et al., 2017; Nedelkoska & Quintini, 2018), require adequately advanced skills that modern automation technology is currently not able to emulate or execute (Oschinski & Wyonch, 2017). Further, Patscha et al. (2017) stressed that, while the increasing automation of routine tasks allows workers to spend more time on carrying out more complex and interesting work tasks, the skill variety that will be demanded from workers will also grow as a result. In view of the aforementioned points, in order to realize this positive picture of automation augmenting human workers and increasing productivity, workers will need to obtain and develop the necessary skills that allow and qualify them to succeed in the future labor market (WEF, 2018). This point is also highlighted by Manyika, Lund, Chui et al. (2017), who argued that as occupations undergo substantial changes in terms of their work tasks, especially when modern automation technology results in the augmentation of certain work activities, workers will frequently have to acquire new skills. In this context, research illustrates the possibly differing effects of the implementation of advanced automation technologies into the workplace by showing the manner in which the two factors job design, which refers to the way work tasks are structured into jobs, and a worker's skill set are complementing recently integrated automation technologies influences potential outcomes for the respective workers (Autor et al., 2000; WEF, 2018). In this sense, workers possessing skills that complement automation technology will likely experience a rise in their job quality (Rajadhyaksha & Chatterjee, 2018; WEF, 2018). On the contrary, although job automation may only impact a specific group of work tasks that make up their job roles, workers devoid of the adequate and necessary skills to adjust to the introduction of new technology and to be able to shift to higher-value work tasks are at risk of experiencing a substantial decrease in job quality (Rajadhyaksha & Chatterjee, 2018; WEF, 2018). In this context, Tytler et al. (2019) stressed that the key for workers is to establish ways to work alongside automation technology and thereby circumvent the risk of being displaced by automation. Accordingly, in order to manage automation effectively and to realize the opportunities associated with modern technology, it is of crucial importance to ensure that workers acquire and develop the relevant skills needed to thrive in the future labor market by, for example, offering adequate possibilities and tools for retraining and upskilling (Shook & Knickrehm, 2017; WEF, 2018). This point will be discussed in more detail in Chapter 4.2.

Overall, the findings presented above illustrate that the modification or restructuring of jobs resulting from modern automation technologies are expected to frequently involve and necessitate the adjustment, modification, and changing of roles, which, in turn, implicate a shift and change in required skills and knowledge (Vazquez et al., 2019). Overall, the majority of employers questioned in the context of the analysis conducted by the WEF (2018) expect that, within the next few years, the skill requirements of a vast number of jobs will undergo substantial changes (WEF, 2018). This is consistent with the argument put forward by Manyika, Lund, Chui et al. (2017), who argued, as already mentioned in the previous chapter, that the anticipated changes in the work tasks or activities required to be performed by human workers will also entail substantial changes in the skill requirements of future jobs.

Summary

To sum up, as the discussion above illustrates, modern job automation technologies do not only have the potential to eliminate certain jobs, but also may promote the creation of new jobs, effectuate a decline or growth of already established jobs, and substantially transform and restructure existing jobs (Manyika et al., 2017; Manyika, Lund, Chui et al., 2017; Nedelkoska & Quintini, 2018; Vazquez et al., 2019; WEF, 2018). As a result, while the net employment effect of job automation technologies may be positive, the reshaping of present jobs as well as the displacement or decline of certain job roles along with the growth or creation of new job roles due to automation may considerably alter or modify the demand for skills (Manyika, Lund, Chui et al., 2017; Servoz, 2019; Vazquez et al., 2019; WEF, 2018). Thus, as occupations are expected to be significantly transformed by the adoption and implementation of modern automation technologies, the corresponding skill requirements for workers are also predicted to undergo substantial changes (Bughin et al., 2018). In light of the arguments presented above, the following section seeks to directly address this prevalent and important question of future skills needs, changes, and demand by reviewing and synthesizing relevant literature in this field. The insights derived from this literature review will not only contribute to answering the central research question of this thesis but will also constitute the discussion base for the subsequent qualitative research study in the form of expert interviews conducted in the realm of the present thesis.

2.4.2 Anticipated Future Skill Trends & Changes in the Skill Requirements of Jobs as a Result of Automation

After having elaborated in detail the underlying dynamics that drive the shifts and changes in skill requirements of jobs in advanced economies within the context of automation throughout the preceding chapters and sections, the subsequent discussion section will provide a comprehensive overview of anticipated general skill trends, changes, and demand that are expected to unfold within the coming years, thereby addressing directly the central research question of the present thesis. For the sake of providing a detailed overview and valuable insights about anticipated future skill shifts within the context of increasingly automated work environments, the following literature review includes the most insightful and important findings derived from relevant and timely literature sources including numerous articles, reports, and empirical research studies. As already mentioned above, these findings derived from the literature will then serve as a basis for the following qualitative research study that is presented and outlined in detail in Chapter 3.

To start with, as reported by Vazquez et al. (2019), both digital and non-cognitive skills, and particularly the combination of both types of skills, will likely increase in demand in the years to come. As remarked by Kirchherr et al. (2018), digital skills refer to “skills that allow people to play an active role in a digitized world” (Kirchherr et al., 2018, p. 5). Further, in terms of the meaning of non-cognitive skills, Vazquez et al. (2019) noted that non-cognitive skills may refer to various notions as cited in the literature including soft skills, human literacy, life skills, or social and emotional skills. In this sense, non-cognitive skills encompass skills relating to “open-mindedness, openness to learn and change, flexibility, curiosity, innovation, creativity, entrepreneurship, resilience, planning/organization, responsibility, persistence, teamwork, communication, initiative, sociability, empathy, collaboration, emotional control and positivity” (Vazquez et al., 2019, p. 31). In terms of the anticipated trend of soft skills, Servoz (2019) argued that, in a labor market progressively influenced by automation, soft skills will increase in importance as the capacity of sophisticated technologies, such as artificial intelligence, is not yet able to adequately emulate such inherently human skills. As noted by Servoz (2019), soft skills relate to the interpersonal qualities that allow individuals to perform effective interactions with others and encompass skills, such as communication, teamwork, and problem solving. This anticipated increase in demand for digital and non-cognitive skills, and especially a mixture of both, reflects past changes in the occupational structure in that research suggests that the majority of occupations that have grown in the past few years relate to job roles that demand a combination of both ICT (Information and Communications Technology) use and non-cognitive skills including dealing with customers and teams (Vazquez et al., 2019). In contrast, occupations requiring a low level of digital skills, less social interaction as well as a low degree of emotional competences have experienced a decline (Vazquez et al., 2019). Based on this, research indicates that a moderate level of ICT skills as well as a high level of non-cognitive skills including teamworking and communication are anticipated to be required for the majority of future jobs that are predicted to grow by 2025 (Pouliakas, 2016; Vazquez, 2019). In line with these insights, further research suggests that, in order to succeed and thrive in anticipated future work environments that are generally assumed to be characterized by unknown, unpredicted and changing conditions and circumstances, workers will need to hold or obtain a diverse skill set that includes cognitive and meta-cognitive skills, such as critical and creative thinking, and learning to learn, non-cognitive skills, such as empathy, self-efficacy, and collaboration, as well as digital skills that relate to the use of new information and communication technology (ICT) devices (OECD, 2018; Vazquez et al., 2019). In relation to this, evidence suggests that, besides the importance of acquiring and developing digital skills in order to adequately meet the anticipated future skill needs, solely focusing on the development of digital literacy will not be sufficient (Cedefop, 2017). In this regard, data from a Cedefop European skills and jobs survey suggests that future jobs are expected to increasingly require the combination of digital and technical skills, as well as soft and behavioral skills, such as problem solving, learning, and communication (Cedefop, 2017). However, in spite of the importance of possessing digital skills in order to succeed in the future labor market, various employers argue that a significant proportion of workers do not appear to be prepared for the increasing demand for digital skills (Vazquez et al., 2019). Underlying this issue, Curtarelli et al. (2016) reported that approximately 15% of employers propose that a substantial share of their employees is not sufficiently skilled in performing work tasks that include the usage of digital technologies. According to the respective employers, this issue reflects the presence of a digital skills gap across their workforce (Curtarelli et al., 2016; Vazquez et al., 2019).

Further, in the realm of their study, Bakhshi et al. (2017) sought to predict the future skill demand in US (United States) and UK (United Kingdom) economies by 2030 as a response to identified determining factors of labor market change including job automation in the context of technological change. More specifically, in order to determine which kind of skills will feature prominently in the future and which ones will experience a decline in future demand, the authors utilized data from the O*NET (Occupational Information Network) database and followed an innovative approach employing both expert human judgement as well as specific machine-learning techniques. Thus, while analyzing the relationship between certain skills as found in the O*NET database and their future demand, Bakhshi et al. (2017) found that, in general, interpersonal skills, higher-order cognitive skills, as well as systems skills will likely feature prominently in both the US and the UK. More specifically, the authors observed that interpersonal competencies including skills, such as instructing, teaching, social perceptiveness, and coordination will likely grow in demand in the future. In addition, the findings highlight the future significance of higher-order cognitive skills including originality and fluency of ideas (Bakhshi et al., 2017). In terms of higher-order cognitive skills, the authors also found that skills associated with learning strategies and active learning, which refer to "the ability of students to set goals, ask relevant questions, get feedback as they learn and apply that knowledge meaningfully in a variety of contexts" (Bakhshi et al., 2017, p. 66), will also grow in significance (Bakhshi et al., 2017). According to the authors, active learning relates to comprehending the implications of novel information with regard to both present and future problem solving and decision-making (Bakhshi et al., 2017). Moreover, skills associated with system thinking, which refers to "the ability to recognize, understand and act on interconnections and feedback loops in sociotechnical systems" (Bakhshi et al., 2017, p. 14), while also describing "a mindset to think, communicate and learn about systems to make the full patterns clearer, improve and share the understanding of problems and see how to face them effectively" (Oliveri, 2020, p. 1), and includes skills such as judgement and decision-making, systems analysis, and systems evaluation, will likely be of high importance in the future (Bakhshi et al., 2017). As argued by Bakhshi et al. (2017), while the term "sociotechnical systems" commonly refers to "interaction between society's complex infrastructures and human behavior" (Bakhshi et al., 2017, p. 14), it can also be deployed to refer to "the relationship between humans and technology in the workplace" (Bakhshi et al., 2017, p. 14). Further, the notion "systems analysis" refers to "determining how a system should work and how changes in conditions, operations and the environment will affect outcomes" (Bakhshi et al., 2017, p. 14), while the notion "systems evaluation" means "identifying measures or indicators of system performance and the actions needed to improve or correct performance, relative to the goals of the system" (Bakhshi et al., 2017, p. 14). While it is anticipated that the skills cited above will all feature prominently in the future, Bakhshi et al. (2017) also identified skills that will likely decrease in demand in the future. In this regard, the findings suggest that skills related to psychomotor and physical abilities, which include skills such as finger dexterity and manual dexterity, will likely decline in demand (Bakhshi et al., 2017).

Further, in terms of anticipated future skill trends, the analysis conducted by the World Economic Forum (WEF, 2018) also yielded some noteworthy findings. While the findings suggest a likely decrease in demand for skills including manual skills, physical abilities, as well as skills concerned with the management of financial and other resources together with basic technology installation and maintenance skills, a different set of skills is expected to grow in demand (WEF, 2018). The skills anticipated to increase in demand within the near future encompass, but are not limited to, analytical thinking and innovation in addition to skills related to active learning and learning strategies as well as to technology design and programming (WEF, 2018). The anticipated strong increase in relevance and importance of skills relating to technology design and programming underlines the rising demand for different types of technology competency recognized by respondents in the survey (WEF, 2018). However, the findings also illustrate that, besides a growing importance of various skills and competencies regarding new technologies, skills relating to inherently human skills, such as creativity, originality, as well as initiative, critical thinking, persuasion, and negotiation are also expected to grow in relevance (WEF, 2018). Likewise, skills encompassing attention to detail, resilience, flexibility, complex problem-solving, emotional intelligence, and leadership in addition to social influence and service orientation are also highly likely to experience an upsurge in demand (WEF, 2018).

Moreover, as already argued in the previous chapter, automation is expected to considerably alter the mix of work tasks that are performed by humans as certain tasks will be carried out by automation technology (Manyika, Lund, Chui et al., 2017). In this regard, the findings established by Manyika, Lund, Chui et al. (2017) suggest that, in the future, an increasing number of work tasks or work activities that will be performed by humans will demand in particular social and emotional skills and advanced cognitive skills, such as high-level logical reasoning. At the same time, the analysis conducted by Manyika, Lund, Chui et al. (2017) indicates that, in advanced economies, physical skills are highly likely to decrease in demand.

In addition, within the realm of their study, Bughin et al. (2018) sought to identify future skill trends in the United States (US) along with a selected set of 14 Western European countries by having determined the current demand for skills employed by the workforce at present and then, based on that, analyzed how this demand could change by 2030 due to the adoption and implementation of modern automation technologies, such as artificial intelligence, into the workplace. In view of this, the researchers' analysis suggests substantial changes in workforce skills as certain skills are expected to become increasingly relevant in an increasingly automated work environment (Bughin et al., 2018). In this regard, the authors found that the greatest expected shift in skill demand will occur in the domain of technological skills including both advanced technological skills that comprise skills relating to programming, sophisticated data analysis, and tech design, among others, as well as more basic technological skills associated with the growing diffusion and importance of digital technologies in many workplace environments (Bughin et al., 2018). In this context, the findings suggest that, while the demand for technological skills experienced a rise since 2002, this demand is expected to considerably accelerate in the time between 2016 and 2030 (Bughin et al., 2018). In particular, the analysis implies that the overall time workers will have to spend on these skills will increase rapidly as the adoption of automation technology by companies progresses. In this regard, the researchers found that time devoted on advanced technological skills is expected to grow by 50 percent in the US as well as by 41 percent in Europe (Bughin et al., 2018). In this context, Bughin et al. (2018) also found that the need for distinct advanced technological skills varies. In view of this, while the researchers anticipate the most rapid increase in the demand for advanced IT and programming skills, skills related to advanced data analysis and mathematics, technology design, engineering and maintenance, as well as scientific research and development are also expected to increase in demand, albeit not in the same intensity (Bughin et al., 2018). Further, the analysis also indicates that basic digital skills constitute the second fastest-growing skill category across the 25 skills analyzed in the study (Bughin et al., 2018). In particular, these skills are expected to rise in demand by 69 percent in the US along with 65 percent in Europe (Bughin et al., 2018). In addition, the analysis indicates that a variety of social and emotional skills are also anticipated to experience a considerable rise in demand (Bughin et al., 2018). In this regard, consistent with the findings established in terms of technological skills, the analysis implies a significant acceleration in the demand for social and emotional skills by 2030 (Bughin et al., 2018). In this respect, the analysis suggests that the future workforce is anticipated to devote significantly more time on employing social and emotional skills than it does at present. More specifically, the researchers found that, overall, the demand for social and emotional skills is expected to increase throughout all industries by 26 percent in the US as well as by 22 percent in Europe (Bughin et al., 2018). In this context, the findings also illustrate that entrepreneurship and initiative taking are predicted to experience the most rapid growth in demand, while other skills including leadership and the management of others are also anticipated to see substantial growth in demand (Bughin et al., 2018). Moreover, the findings suggest that the demand for cognitive skills is expected to shift from basic towards higher cognitive skills (Bughin et al., 2018). In other words, the analysis implies a shift from work tasks that demand merely basic cognitive skills towards work activities that demand the deployment of higher cognitive skills (Bughin et al., 2018). In fact, it is expected that the decrease in tasks that predominantly demand basic cognitive skills will be the most significant throughout the five skill categories analyzed by the researchers (Bughin et al., 2018). In this regard, as it is anticipated that the need for higher cognitive skills including creativity, critical thinking along with decision making, and complex information processing will increase by 2030, the analysis in particular suggests an increase in demand for those skills by 19 percent in the US together with 14 percent in Europe given today's level of demand (Bughin et al., 2018). To illustrate, the researchers noted that the predicted rise in demand for creativity is visible in various work activities, such as the configuration of high-level marketing strategies, while the growing demand for complex information processing, for example, is associated with the necessity to stay abreast of specific market trends along with the regulatory forces that may influence the business operation, or the necessity to be able to make sense of and inform customers about technical issues regarding certain products and services (Bughin et al., 2018). In relation to this, the analysis also indicates that certain higher cognitive skills including advanced literacy and writing as well as quantitative and statistical skills are not predicted to experience an equivalent growth in demand and in fact, may maintain a certain stability or even see a decrease in demand by 2030 (Bughin et al., 2018). This may be explained by the fact that, for example in writing and editing, modern technology already possesses a certain proficiency that enables it to write, for instance, simple news stories (Bughin et al., 2018). Nevertheless, the authors emphasized that, even though these skills may experience a decline, there will still be a future demand for, for example, authors or writers, due to the rationale that, as thoroughly illustrated in the previous chapters and sections, it is mostly certain tasks of a specific job role that are affected by automation (Arntz et al., 2016; Bughin et al., 2018; Vazquez et al., 2019). Consistent with the above-mentioned anticipated changes regarding the trend of and demand for social and emotional skills along with advanced cognitive skills, the findings obtained through Cedefop's European skills and jobs survey also suggest that there will be substantial changes in skill demands as a result of predicted job restructuring (Cedefop, 2018). More specifically, the findings imply that both advanced cognitive skills, such as literacy, numeracy, problem-solving, and learning, as well as socioemotional skills including communication, teamworking, planning, and customer service skills are expected to become increasingly relevant in the near future (Cedefop, 2018). To continue, in terms of basic cognitive skills, Bughin et al. (2018) pointed out that the anticipated absence of an increase in demand for basic quantitative and statistical skills may indicate the proficiency of specific automation technology to perform various back-office activities, for instance in financial reporting, tax calculation, or accounting (Bughin et al., 2018). In this regard, the authors noted that certain algorithms together with robotic process automation, which commonly refers to "a software solution that mimics a variety of rules-based, repeatable processes that don't require real-time creativity or judgement" (Bovaird et al., 2017, p. 5), may perform those work activities in a much more efficient way (Bughin et al., 2018). Moreover, according to the analysis, as automation is progressing, work tasks that solely demand basic cognitive skills will especially experience a decline in demand (Bughin et al., 2018). In this regard, the researchers noted that simple data input and processing skills will be particularly impacted by automation, with a predicted decrease in demand by 19 percent in the US and 23 percent in Europe by 2030 (Bughin et al., 2018). In this context, the analysis predicts that this anticipated decline in basic data input and processing skills constitutes, together with general equipment operation and navigations as well as inspecting and monitoring, the strongest reduction across the 25 skills investigated (Bughin et al., 2018). According to Bughin et al. (2018), the main explanation for this predicted decline presents the anticipated decline in demand for basic data processing, which features a large degree of susceptibility to automation and is evident throughout many sectors. Further the findings indicate that, in contrast to data processing, skills regarding basic literacy, numeracy, and communication are expected to, in general, stay relevant, yet are predicted to not being sufficient to meet the requirements of the future labor market without the acquisition or possession of additional skill sets (Bughin et al., 2018). Finally, Bughin et al. (2018) found that physical and manual skills are anticipated to proceed to decline in demand, as they did throughout the years, albeit they are expected to continue to constitute a significant element of the future workplace. More specifically, all in all, these kinds of skills are predicted to see a decrease in demand by 11 percent in the US as well as by 16 percent in Europe by 2030 (Bughin et al., 2018). In this context, the researchers also pointed out that changes in the demand for physical and manual skills are predicated on the degree of susceptibility to automation of the works tasks that the respective occupation encompasses (Bughin et al., 2018). For instance, operating vehicles or stocking and packaging products display a higher risk of being automated compared to providing assistance to patients in healthcare settings or cleaning work (Bughin et al., 2018). In this regard, Bughin et al. (2018) found that general equipment operation and navigation, which refer to skills employed by manufacturing assembly workers or drivers, along with skills related to inspecting and monitoring are expected to decrease more rapidly in demand compared to other skills within this skill category of physical and manual skills (Bughin et al., 2018). Noteworthy to mention at this point is that the analysis further implies that this general downward trend concerning the need for physical and manual skills is not expected to be visible in all sectors as, for example, within the US healthcare sector, the demand for gross and fine motor skills is predicted to grow by around 30 percent due to the assumption that an aging population fosters the need for work activities associated with, for instance, nursing and physical therapy (Bughin et al., 2018). In addition, as already indicated above, the findings suggest that, despite the anticipated continuing decline in demand for physical and manual skills, this skill category is still expected, based on the evaluation of the time spent on these skills, to remain the largest category across all skill categories (Bughin et al., 2018). Moreover, concerning the adoption of automation technologies in the workplace, the analysis conducted by Bughin et al. (2018) suggests that the rate of adoption of automation technology would not significantly alter the anticipated skill trends presented above. In particular, the authors found that, in the case that adoption would be more rapid or much slower compared to the median baseline assumed by the researchers in the realm of their analysis, the general trends identified would not significantly change even though, in the case of a faster rate of automation adoption, physical and manual skills along with basic cognitive skills would experience a more rapid decrease in demand, while the demand for social and emotional skills in addition to higher cognitive skills would increase in a much faster pace (Bughin et al., 2018).

Further, in terms of anticipated future skill trends, the Australian Industry Group (AIG) (2018) also emphasized that the considerable changes expected to result from automation as thoroughly discussed in the previous section will necessitate a shift in skills that the future workforce is required to possess in order to keep up with the changing nature of work due to automation. More specifically, digital literacy skills, specific management capabilities, as well as skills associated with the field of STEM (Science, Technology, Engineering, and Mathematics) along with enterprise and entrepreneurial skills were all cited as being expected to increase in importance within the next few years (AIG, 2018). According to the AIG (2018), STEM skills will be in high demand for a large number of future higher-skilled jobs. In this regard, as modern automation technologies are further progressing and becoming increasingly complex, skills related to the domain of STEM will increasingly be demanded as an entry level requirement (AIG, 2018). Moreover, AIG (2018) reports that, given that enterprises and entrepreneurs constitute leading factors underlying a substantial share of the innovation, productivity gains, as well as novel opportunities for employment in the current business context in addition to being essential determinants for economic growth, workers possessing these kinds of enterprise and entrepreneurial skills will be increasingly required in today's digital economy (AIG, 2018; Foundation for Young Australians, 2016). The increasing relevance of well-developed entrepreneurial skills is also underlined by Oschinski & Wyonch (2017) who stressed that, while discussing some important implications of increasingly automated workplaces, it is becoming more and more substantial to encourage and develop an entrepreneurial mindset among new workforce entrants. According to Oschinski and Wyonch (2017), workers will increasingly have to deal with a much more disruptive environment where it is essential for workers to possess the relevant skills and abilities to recognize problems and to react in a value-adding manner. The authors emphasized that, as, in general, future occupations are expected to entail higher skill requirements, there will be the need for workers to respond, adjust, and make decisions in the absence of regular information or input from managers (Oschinski & Wyonch, 2017). Enterprise skills, which are also frequently cited as "21st century" skills or "transferable" skills that can be utilized throughout various job roles and occupations, refer to skills that allow individuals to deal with complex environments and to manage the challenges associated with the anticipated future changes brought about by automation (AIG, 2018; Foundation for Young Australians, 2016). As noted by Deloitte (2017), transferable skills can be described as skills "that can be applied in varied contexts" (Deloitte, 2017, p. 4). For instance, a skill that is thought to be relevant and valuable across different jobs or industries that entail differing contexts can be classified as a transferable skill (Deloitte, 2017). This being said, according to AIG (2018), enterprise skills include skills related to problem solving, communication, digital literacy, teamwork, as well as critical thinking along with creativity and thus, encompass higher-level thinking skills (AIG, 2018). As found by the Foundation for Young Australians (2016), future jobs will require enterprise skills in a much higher frequency compared to previous jobs. Thus, the findings indicate that enterprise skills will become increasingly important in the years to come (Foundation for Young Australians, 2016). In relation to the aforementioned points, Dawson (2017) emphasized that individuals that acquire and develop high levels of transferable and flexible skills including skills related to digital literacy, STEM, and problem solving will more easily adapt and manage the changes within the labor market. In addition, as reported by the AIG (2018), workers holding a strong level of entrepreneurial skills possess the capacity to sufficiently understand current as well as future trends and needs and are able to utilize this understanding to originate novel and productive ideas that may effectively contribute to the establishment and implementation of organizational innovations (AIG, 2018).

Moreover, Tytler et al. (2019), who, conducted an interview study with the aim to yield insights regarding the types of skills that will likely grow in demand in the near future, found that many of the interview respondents anticipate an increasing relevance of the possession of cross-disciplinary skills. For instance, the interview respondents argued for a growing importance of conjoining disciplinary knowledge with skills relating to technology as a means to be able to make sense of data and data needs (Tytler et al., 2019). Further, the importance of workers having the capacity to work throughout disciplinary fields, such as fields related to STEM, technology, as well as creativity, also reflects the increasing relevance of holding cross-disciplinary skills (Tytler et al., 2019). This point is also underlined by Riad (2017), who argued that, while higher-order cognitive skills, such as numeracy, literacy, and problem solving, are increasing in importance with a growing level of an "economy's technological sophistication" (Riad, 2017, p. 17), soft skills that cannot be adequately replicated by even advanced technology including teamwork, creativity, adaptability, as well as social and cultural awareness are equally relevant. In view of this, Riad (2017) pointed out that future jobs will "marry science and art, so that humans can work with machines and not against them" (Riad, 2017, p. 18). In addition, respondents in the study conducted by Tytler et al. (2019) commonly agreed that inherently human skills will likely increase in importance within the next few years. In this regard, it is expected that emphasis will increasingly shift towards understanding and communicating with others, as well as towards working in teams (Tytler et al., 2019). In view of the aforementioned points, the Australian Industry Group (AiGroup, 2018) argued that, within the context of technology rich work environments, a number of skills will become increasingly relevant. First, workers will need to develop their proficiency in being able to work in close collaboration with technology, which stresses the importance for workers to develop advanced technological skills (AiGroup, 2018). Second, workers will need to be increasingly skilled in problem solving, critical thinking, as well as analytical skills (AiGroup, 2018). In addition, as the jobs of many workers are expected to experience substantial changes due to automation, skills associated with agility, resilience, and flexibility will be pivotal for workers to acquire or develop as such skills will assist workers in succeeding in even highly complex and unpredictable work environments (AiGroup, 2018). In relation to this, the findings obtained by Tytler et al. (2019) clearly illustrate that, within the next few years, which are anticipated to involve many changes in the world of work due to increasing automation, skills related to flexibility and adaptability will, too, become increasingly important. In this regard, the researchers emphasized that the ability to learn will be essential for workers to succeed in the future labor market and thus, a growing emphasis on lifelong learning will be needed to ensure that workers acquire and continue to develop the skills required to thrive in increasingly dynamic and automated work environments (Tytler et al., 2019). Chapter 4.2.2 will discuss this point in more detail.

To continue, the study conducted by the Pew Research Center and Elon University's Imagining the Internet Center also provided a number of interesting insights concerning anticipated future skill trends and changes within the context of automation (Rainie & Anderson, 2017). First, respondents in the study commonly agreed that soft, uniquely human skills that prove to be difficult for even sophisticated machines to replicate will become increasingly important in the age of sophisticated automation technologies including artificial intelligence and robotics (Rainie & Anderson, 2017). In this regard, one study respondent argued that skills including emotional intelligence, empathy, compassion, human meta communication, leadership, cooperation, innovation, and creativity will increase in relevance and thus, will be valuable skills for workers to possess and develop (Rainie & Anderson, 2017). In relation to this, another study respondent stressed that, in the future, greater emphasis will be placed on skills that prove difficult for even sophisticated technology to emulate or replicate including creativity, taking initiative, multi-disciplinary thinking, as well as empathy (Rainie & Anderson, 2017). Further, responses collected in the realm of the study suggest that skills related to system-thinking and adaptability will also become increasingly important in order to succeed in a dynamic and ever-evolving work environment (Rainie & Anderson, 2017). This point is consistent with the findings obtained by Patscha et al. (2017), who found that, within complex work environments, developing strong levels of systemic thinking will become increasingly important in order to "allow tasks to be understood in their wider context, and challenges in flexible value-adding networks to be considered critically and solved creatively (Patscha et al., 2017, p. 33). To continue, study respondents surveyed in the realm of the study conducted by Rainie and Anderson (2017) also commonly agreed that skills associated with programming, problem solving, as well as the capacity to interact and engage with new technologies including robotics and artificial intelligence will grow in importance throughout the next few years (Rainie & Anderson, 2017). Moreover, the study insights also indicate that the skill to continue to learn will be essential in all future jobs (Rainie & Anderson, 2017).

To continue, in 2017, the Foundation for Young Australians (FYA) published their report "The New Work Smarts", in which it presented the findings from their study that analyzed the types of skills that will be most relevant by 2030 in increasingly automated workplaces (FYA, 2017). In particular, the FYA (2017) analyzed how the work activities currently performed by

Australians will change by 2030. As elaborated in the previous chapter, these insights or forecasts regarding future trends of work tasks that are carried out by human workers entail important implications for future skills required to succeed in increasingly automated workplaces of the future (see e. g. FYA, 2017; Manyika, Lund, Chui et al., 2017; Servoz, 2019; Vazquez et al., 2019; WEF, 2018). As argued by the FYA (2017), the forecasts about future jobs and associated work tasks will determine the relevant skills needed for workers to thrive in future labor markets. With regard to this, the findings obtained by the study yielded some interesting insights regarding expected future skill trends (FYA, 2017). Overall, the findings illustrate that, by 2030, workers will need to hold a diverse portfolio of different skills in order for them to succeed in the future world of work (FYA, 2017). In particular, workers need to be problem solvers and critical thinkers, they have to be good communicators and engagers, and they need to be educated in science, mathematics, and technology (FYA, 2017). Regarding the importance for workers to be good problem solvers and critical thinkers, the findings obtained by the analysis conducted by the FYA (2017) suggest that the skills that will be most relevant in future workplaces encompass problem solving, as well as judgement and critical thinking, which include developing innovative means of doing things in a different way, experimenting with novel ideas, and testing hypotheses. With regard to this, the FYA (2017) provides the example of care workers, which will need to become more autonomous problem solvers by 2030. In particular, despite the fact that many care jobs are generally understood to be less affected by automation in the years to come, the analysis conducted by the FYA (2017) indicates that their skill demands will undergo substantial shifts by 2030. More specifically, it is expected that automation will be increasing the time spent on deploying interpersonal skills in addition to skills related to critical thinking and problem solving (FYA, 2017). Moreover, with regards to the importance of workers being well-versed communicators and engagers, the findings propose that, in the future, workers will generally need to be proficient at working with others in order to thrive in their future job roles (FYA, 2017). In particular, it is anticipated that future jobs will require good levels of written and verbal communication along with interpersonal skills (FYA, 2017). Lastly, in terms of the value for future workers to be sufficiently educated in the domains of science, mathematics, and technology, the study's insights revealed that, in general, future workplaces will demand high levels of foundational skills in science and mathematics, as well as high levels of skills related to advanced technology (FYA, 2017). In relation to this, the findings suggest that, due to the prediction that even in future jobs that are strongly based on science and mathematics, communication skills as well as interpersonal skills will equally be of high importance, workers of the future must possess high levels of both STEM skills in addition to enterprise skills including problem solving, critical thinking, and communication in order to be adequately prepared for future job requirements (FYA, 2017). Thus, the sole possession of well-developed STEM skills will not be sufficient to thrive in future work environments as adequate levels of enterprise skills are needed in order to effectively realize and communicate ideas and solutions (FYA, 2017). Further, regarding the combination of diverse skills, Ovanessoff et al. (2018) found that, as the nature of work is experiencing a significant transformation due to the advent of intelligent automation technologies that are effectuating changes in job roles, work tasks, and skill requirements of the job roles, the future world of work is increasingly demanding a combination of complex reasoning, creativity, social and emotional intelligence, as well as sensory perception skills. Whereas complex reasoning encompasses skills related to critical thinking, active learning, and higher-order cognitive skills, social and emotional intelligence includes active listening, persuasion, and negotiation skills, among others (Ovanessoff et al., 2018). Further, according to the authors, sensory perception skills include "a wide range of sensory capabilities that have been stimulated through our increasingly intimate relationship with digital technologies" (Ovanessoff et al., 2018, p. 15). In addition, and in view of the insights concerning important future skills mentioned above, Dawson (2017) emphasized that, despite the crucial importance for workers to possess sufficiently high levels of technology skills, skills including customer service, collaboration, and curiosity will be equally important. With regard to this, Dawson (2017) argued that, regardless of the upcoming advances in technology, customer service will always remain a highly valued skill. Moreover, according to Dawson (2017), in order to build up value within this increasingly complex world we live in, collaboration skills will be highly relevant as this allows workers to work in close collaboration with others, thereby combining the workers' unique and distinct skills. In addition, Dawson (2017) stressed that a curious mindset will empower and motivate workers to continue to learn. As underlined by Dawson (2017), workers need to possess the ability to learn in order for them to adequately manage and respond to continuous change. Overall, Dawson (2017) emphasized that, as work and jobs are undergoing substantial changes due to automation, a shift in the skills needed to thrive in this complex and dynamic world of work will be taking place. More specifically, the author emphasized that within the coming years, workers will need to increasingly shift their emphasis on uniquely human skills that differentiate us from modern automation technology, such as creativity, imagination, emotional intelligence, and empathy

(Dawson, 2017). Consistent with this, Kosslyn (2019) argued that human emotions are particularly difficult for machines to emulate. According to Kosslyn (2019), emotions are not only a substantial element of nonverbal communication and is strongly associated with human empathy but is also involved in the decision-making of individuals. Thus, due its complex and nuanced nature, skills associated with emotion prove difficult to be emulated by an automated system (Kosslyn, 2019). Further, as noted by Kosslyn (2019), developing or designing machines in a way so that they are able to take a specific context into account also proves incredibly challenging. While it is rather simple for humans to take into account a specific context when interacting with others or when making decisions, it is a challenging endeavor for even sophisticated automation technologies to adequately emulate skills associated with taking certain contexts into account (Kosslyn, 2019). In terms of both emotions and contexts, Kosslyn (2019) stressed that an individual's proficiency in being skilled at both handling and using their emotions as well as taking into account different contexts is strongly associated with inherently human skills, such as skills related to critical and creative thinking, complex problem solving and communication, along with learning and judgement skills. Overall, it seems extremely challenging to design and program machines in way that allow them to adequately emulate such uniquely human skills (Kosslyn, 2019). Accordingly, as argued by Dawson (2017), in a future world of work, in which a wide range of automation technologies will be increasingly utilized, the most meaningful and valuable work will place particular emphasis on uniquely human skills (Dawson, 2017). Lastly, and consistent with the aforementioned points, the World Economic Forum (WEF) (2020) found that, within the context of increasingly automated work environments, skills associated with analytical thinking and innovation, active learning and learning strategies, complex problem-solving, critical thinking and analysis, creativity, flexibility, emotional intelligence, systems analysis and evaluation, as well as technology use, monitoring and control skills together with technology design and programming skills count among the top 15 skills for 2025 (WEF, 2020).

Summary of the chapter: Key findings

As demonstrated in the previous section, automation is expected to affect a wide range of occupations in various ways, which, in turn, is anticipated to entail substantial shifts and changes in the skill requirements of jobs. In view of this, the present section sought to build on these findings by addressing in detail the associated anticipated changes in the future demand for skills by synthesizing relevant findings from recent academic literature. In this regard, the following tables and corresponding discussion will summarize the main findings derived from the literature presented above.

For the purpose of providing a clear and coherent summary of the findings presented throughout this chapter in terms of anticipated future skill trends, demands, and changes in the context of increasingly automated future work environments, a classification of distinct skill categories was developed in the realm of the present thesis. However, before elaborating, in further detail, the skill classification developed and used for the purpose of this work as presented in Table 1, it is important to emphasize that different classifications of skills are utilized and employed throughout extant academic literature (see e. g. Allen et al., 2017; Cunningham & Villaseñor, 2014; D2L Corporation, 2019). Cunningham and Villaseñor (2014), for example, distinguished labor market skills between technical, socio-emotional skills, as well as cognitive skills, with the latter further distinguished between lower-order and higher-order cognitive skills. Allen et al. (2017) differentiated skills along the following categories: skills for collaborating, foundational skills, skills for learning and adapting, entrepreneurship skills, analytical skills, skills for adding value, non-automatable skills, and social platform skills. In addition, while Vazquez et al. (2019) further distinguished between cognitive skills, non-cognitive skills, as well as digital skills, the D2L Corporation (2019) differentiated between technical, job-specific skills and so-called durable skills which the authors defined as “the cognitive and non-cognitive skills necessary to engage in, interact with, and adapt to any work environment, including critical thinking, creativity, adaptability, emotional intelligence, and global competencies” (D2L Corporation, 2019, p. 3). Further, Bughin et al. (2018) divided workforce skills into five broad categories: physical and manual skills, basic cognitive skills, higher cognitive skills, social and emotional skills, technological skills. Moreover, The Foundation for Young Australians (FYA, 2017) mainly distinguished between the broad skill categories of foundational skills, which encompass skills like literacy, language, and numeracy, technical skills, which often refer to a specific work task, job role, or industry and may comprise certain qualifications including licenses or certificates, as well as enterprise skills, which, as already argued earlier, refer to transferable skills including problem solving, communication, teamwork, and creativity (FYA, 2017).

The discussion above clearly illustrates that no consistent, standard classification of workforce skills exists, at least to the author’s knowledge, that may be adopted for the purpose of this thesis. Based on this, while drawing inspiration from a variety of literature sources in terms of the development of a comprehensive skill taxonomy, the skill classification developed for the purpose of this thesis as presented in Table 1 nevertheless reflects the author's own thinking, interpretation, and argumentation. With that said, Table 1 provided above presents the skill classification developed and utilized for the purpose of the present thesis. However, it should be emphasized at this point that, even though the skill classification outlined in Table 1 differentiates between distinct skill categories, overlaps in the skills among the differing skill categories may, nevertheless, exist, and, thus, a strict demarcation between the various skill categories in terms of the skills each category encompasses may be difficult to achieve. Further, some difficulties were encountered when seeking to provide proper definitions for each of the skill categories outlined in Table 1. In view of this, even though a wide range of literature was reviewed for the purpose of obtaining timely and valuable literature findings that are considered relevant for contributing to providing an answer to the central research question of this thesis, no specific and coherent definitions for the respective skill categories could be identified that were considered appropriate and useful for the purpose of this work. Nevertheless, as it was deemed essential by the researcher to properly define the skill categories presented in Table 1 in order to contribute to the reader's overall understanding in terms of the central topic at hand, the researcher tried to the best of her ability to identify literature sources, based on which a coherent definition for each skill category could be provided. In view of this, while the discussion of the distinct skill categories presented below integrates some useful descriptions identified from extant literature concerning the various skill categories, it was refrained from including a specific definition for each category in Table 1 due to the above-mentioned difficulties in identifying or locating a clear and coherent definition for each skill category. This being said, Table 1 provides a short overview of the distinct main skill categories along with a non-exhaustive list of associated skills relating to the respective skill category. In view of this, the following discussion will provide a thorough overview and description for each main skill category presented in Table 1.

Table 1: Skills Categorization

Main Skill Category	**Associated Skills (Examples)**
Physical & Manual Skills	▪ finger & manual dexterity ▪ general equipment operation and navigation ▪ gross and fine motor skills

Cognitive Skills (Basic and Advanced)	Basic: ▪ basic quantitative and statistical skills ▪ simple data input and processing skills Advanced: ▪ critical and creative thinking ▪ complex information processing ▪ high-level logical reasoning ▪ learning strategies and active learning
Social & Emotional Skills	▪ teamwork ▪ communication ▪ flexibility ▪ adaptability ▪ entrepreneurial skills
Technological and Digital Skills	▪ technology design and engineering ▪ development of smart hardware & robotics ▪ blockchain technology development ▪ digital learning (the learning of digital skills and utilization of digital technologies) ▪ digital literacy (e. g. coding, cybersecurity)
Systems Skills	▪ systemic thinking, systems analysis, systems evaluation

Sources: AIG (2018); Allen at al. (2017); Bakhshi et al. (2017); Bughin et al. (2018); Cedefop (2017); Cedefop (2018); Ceemet (2018); Daheim & Wintermann (2016); Dawson (2017); Foundation for Young Australians (2016); Kirchherr et al. (2018); Manyika, Lund, Chui et al. (2017); OECD (2018); Oliveri, 2020; Rainie & Anderson (2017); Riad (2017); Servoz (2019); Tytler et al. (2019); Vazquez et al. (2019)

To start with, the first main skill category encompasses physical and manual skills. As argued by Bakhshi et al. (2017), this skill category may also refer to psychomotor and physical abilities, which relate to skills including finger dexterity and manual dexterity (Bakhshi et al., 2017). In general, the domain of physical and manual skills typically includes skills associated with general equipment operation and navigation, as well as skills related to inspecting and monitoring along with gross and fine motor skills (Bughin et al., 2018). In view of this, physical and manual skills generally refer to those skills that demand a physical component, and which typically demand a certain degree of dexterity, motor control, or strength (Atkinson, n. d.). Thus, physical and manual skills are clearly distinguished from cognitive skills that are

commonly associated with thinking or reflection skills as well as from social and emotional skills that generally involve an affective or interpersonal component (Atkinson, n. d.).
While the aforementioned points offer a basic overview of the diverse skills that are commonly associated with the broad skill category of physical and manual skills, identifying or locating a proper definition of this skill category proved to be a rather difficult task as, based on the extant and relevant literature reviewed, no standard definition seems to exist that was considered adequate to cite within this context. Thus, even though scholars or researchers frequently addressed this broad skill domain in their works when seeking to estimate or assess anticipated future skill trends and changes within the context of automation, no coherent or clear definition was provided (see e. g. Bughin et al., 2018). Rather, the literature sources reviewed focused, in general, more on providing a number of skills that are considered to pertain to this broad skill category, of which some are already cited above. The aforementioned points illustrate the difficulties mentioned earlier in identifying and locating clear and coherent definitions for the respective skill categories addressed within the realm of this work. Nonetheless, although no adequate definition could be found, it is still of hope that the descriptions provided above along with the literature review presented earlier that frequently addressed the domain of physical and manual skills provide the reader with a good understanding of what this main skill category of physical and manual skills entails.

To continue, the second main skill category that was frequently acknowledged by academic literature reviewed in the realm of this thesis and that was included in Table 1 presents the category of cognitive skills, which is, consistent with the approach put forward by Bughin et al. (2018), further distinguished between basic and advanced cognitive skills. As will be illustrated shortly when discussing the anticipated future skill trends in the context of increasingly automated work environments, this differentiation is reasonable as it is expected that future trends and demand for basic skills and higher-order cognitive skills will diverge. Generally speaking, cognitive skills enable individuals to remember, reason, hold attention, think, read, learn, solve problems, as well as to process information (Indeed, 2020; Khullar, 2020). In view of this, cognitive skills, which are also frequently referred to as cognitive capacities, cognitive functions, or cognitive abilities, constitute brain-based skills that allow individuals to conduct mental activities that are associated with, along with the areas mentioned above, memory function, perception, decision-making, interpreting data, as well as language abilities (Khullar, 2020). In terms of the distinction between higher-order and lower-order cognitive skills, higher-order or advanced cognitive skills constitute complex cognitive skills that typically go beyond basic cognitive skills, such as simple memory function (Thought Leaders, n. d.). In view of this differentiation, the cognitive skills taxonomy proposed by Bloom (1956), which is officially referred to Bloom's Taxonomy of cognitive domains, helps to comprehend this proposed distinction between basic or lower-order and advanced or higher-order cognitive skills (Thought Leaders, n. d.). Shortly speaking, this taxonomy classifies cognitive domains into six different levels that comprise, as a first level, knowledge and then proceeds, according to their attributed complexity, with the domains of comprehension, application, analysis, synthesis, and evaluation (Bloom, 1956; Crowe et al., 2008; Krathwohl, 2002). Anderson et al. (2001) revised Bloom's original taxonomy by converting the main domain terms into their associated verb equivalents. Hence, with respect to each cognitive domain cited by Bloom (1956) that signal a certain level of complexity ranging from very simple to very advanced, Anderson et al. (2001) converted these into the verbs of remember, understand, apply, analyze, create, and evaluate (Crowe et al., 2008). In light of this, this cognitive skills framework begins with very basic cognitive skills, which, according to this taxonomy, are related to the skills of remembering and understanding, and then proceeds to more complex cognitive skills relating to applying and analyzing. The cognitive skills with the highest degree of complexity constitute, according to this framework, skills related to evaluating and creating (Anderson et al., 2001; Thought Leaders, n. d.). As already indicated above, this taxonomy may provide the reader with an idea and improved understanding of the classification of cognitive skills into basic and advanced cognitive skills (see e. g. Thought Leaders, n. d.). This may be especially helpful and valuable as, as concluded by the researcher when reviewing relevant literature for the purpose of providing a clear and coherent definition for not only the broad domain of cognitive skills, but also the more nuanced domains of basic and advanced cognitive skills, no systematic definitions relating to the aforementioned categories seem to exist that were considered appropriate to be adopted within this context. Nevertheless, it still is in the researcher's hope that the descriptions of cognitive skills as well as their subcategories of basic and advanced cognitive skills, along with the short overview of Bloom's (1956) taxonomy of cognitive domains presented above provide the reader with a good idea about this skill category of cognitive skills.

This being said, while basic or lower-order cognitive skills typically comprise skills, such as basic quantitative and statistical skills, as well as simple data input and processing skills (Bughin et al., 2018; Thought Leaders, n. d.), higher-cognitive skills, which are sometimes also referred to as meta-cognitive skills, higher-order cognitive skills, or advanced cognitive skills (Bakhshi et al., 2017; Manyika, Lund, Chui et al., 2017; OECD, 2018; Vazquez et al., 2019) typically encompass skills including critical and creative thinking, advanced literacy and writing, decision-making, problem solving, complex information processing, originality, fluency of ideas, high-level logical reasoning, learning strategies and active learning (Bakhshi et al., 2017; Bughin et al., 2018; Greiff et al., 2015; Manyika, Lund, Chui et al., 2017; OECD, 2018; Vazquez et al., 2019).

To continue, the third skill category constitutes the social and emotional skills, which other academic literature sources may also at times refer to as non-cognitive skills, soft and behavioral skills, life skills, interpersonal skills, or socio-emotional skills (Bakhshi et al., 2017; Bughin et al., 2018; Cedefop, 2017; Cedefop, 2018; Vazquez et al., 2019). In terms of the notion of social and emotional skills, it is argued that social skills along with emotional skills entail a high degree of interrelation, based on which, the notion of *social and emotional skills* was formed (Mentalup, 2020). However, even though the literature sources reviewed and utilized for the purpose of developing the extensive literature review presented earlier commonly address social and emotional skills in their works when addressing the anticipated future relevance of and demand for skills pertaining to the category of social and emotional skills, none of these sources provided an adequate definition or description of the category of social and emotional skills that could be utilized for the development and creation of the skill classification presented in Table 1. Nevertheless, as it was deemed essential to provide a coherent and proper definition for each skill category presented in Table 1 for the sake of contribution to the reader's understanding of the central topic at hand, a number of attempts to define or describe this category will, even though in the face of the challenge to identify a proper definition based on extant literature, still be provided below in order to provide the reader with a general understanding and idea of the nature and character that this skill category along with its associated skills entail.
In view of this, while social skills generally refer to "developed capacities used to work with people to achieve goals" (O*NET, n.d.), emotional skills may be described as "essential social skills to recognize, interpret, and respond constructively to emotions in yourself and others" (Beaumont, n. d., p. 1). As already indicated above and as these two definitions provided above illustrate, social skills as well as emotional skills or competence seem to be highly interwoven, which justifies the fact that these two skill categories are combined into one broad skill category

for the purpose of this thesis, thereby following the approach of a number of scholars cited throughout this chapter (see e. g. Bughin et al., 2018). Overall, it may be argued that the category of social and emotional skills encompasses skills necessary for individuals to recognize and control their emotions and behaviors, to care and develop concern for others, to make appropriate decisions, establish and maintain positive relationships, as well as to manage challenging situations in an adequate manner, along with to determine and achieve positive goals" (National Mentoring Resource Center, n. d.; Zins & Elias, 2007).

In view of this, as already indicated throughout this chapter, this broad skill category of social and emotional skills encompasses skills associated with teamwork, communication, human meta communication, emotional intelligence, collaboration, empathy, compassion, flexibility, adaptability, continuous learning, teaching, leadership, customer service, coordination, social perceptiveness, as well as entrepreneurial skills that generally refer to transferable skills that allow individuals to deal with complex environments and to manage the challenges associated with the anticipated future changes as already noted earlier and encompass skills related to problem solving, communication, teamwork, and creative thinking (AIG, 2018; Bakhshi et al., 2017; Bughin et al., 2018; Cedefop, 2018; Dawson, 2017; Foundation for Young Australians, 2016; Rainie & Anderson, 2017; Riad, 2017; Servoz, 2019; Tytler et al., 2019; Vazquez et al., 2019). As the aforementioned points illustrate, the category of entrepreneurial skills, that, for the purpose of this thesis was included as a skill subcategory of social and emotional skills, also encompasses, by its nature, skills that, in view of the classification presented in Table 1, not only may be attributed to the category of social and emotional skills, but also to the category of advanced cognitive skills. This issue reflects the point mentioned earlier, through which it was argued that, in terms of the development and provision of a clear skill classification, a clear demarcation between the distinct skill categories and their associated skills may be difficult, or even impossible, to achieve. Thus, with regards to the description in terms of entrepreneurial skills, it needs to be acknowledged that, enterprise skills also comprise skills that generally belong to the category of higher-level thinking skills as emphasized by the AIG (2018). Nevertheless, following Bughin et al. (2018), for the purpose of the present thesis, the category of entrepreneurial skills is included under the broad category of social and emotional skills.

Further, the domain of technological and digital skills presents another main skill category as illustrated in Table 1 presented above. As already indicated earlier, certain difficulties were encountered when seeking to provide appropriate or relevant definitions for the main skill categories identified and discussed within the context of the present thesis, with those difficulties especially applying to the task of defining or describing the broad category of technological and digital skills. While a number of scholars and researchers do offer some descriptions relating to the skill category of technological and digital skills (see e. g. Kirchherr et al., 2018), it was, nevertheless, considered extremely difficult to locate or identify a relevant definition that was evaluated to adequately and coherently depict or describe the category of technological and digital skills along with their associated skills, also due to the fact that many researchers or scholars view technological skills as synonymous to digital skills, and vice versa (see e.g. Bughin et al., 2018). Nevertheless, despite this challenge of providing an adequate definition for the purpose of the present work, a number of verbal attempts made by scholars and researchers to describe or define this skill category will be provided in the following. For example, as argued by Kirchherr et al. (2018), "technological skills cover those skills that are needed to shape transformative technologies" (Kirchherr et al., 2018, p. 5), while digital skills refer to "skills that allow people to play an active role in a digitized world" (Kirchherr et al., 2018, p. 5). Further, as argued by Daheim and Wintermann (2016), technological and digital skills refer to skills that enable individuals to deal with, understand, and control technology, while Ilomäki et al. (2011) noted that digital competence constitutes a "most recent concept describing technology-related skills" (Ilomäki et al., 2011, p. 1). In addition, UNESCO (2018) defined digital skills as "a range of abilities to use digital devices, communication applications, and networks to access and manage information. They enable people to create and share digital content, communicate and collaborate, and solve problems for effective and creative self-fulfillment in life, learning, work, and social activities at large" (UNESCO, 2018, p. 1), while Kispeter (2018) referred to basic digital skills as basic digital literacy skills and argued that basic digital literacy skills can be distinguished into four categories, with the first category encompassing the understanding of digital information and communication, the second category depicting IT management, the third category relating to managing information, and the fourth category constituting digital communication.

As the aforementioned discussion illustrates, a variety of descriptions exist that aim to describe or define the broad category of technological and digital skills. However, the author concludes from reviewing the relevant literature in this field that no standard working definition of this skill category exists that, according to the author's viewpoint, accurately depicts the different nuances and depths that this skill category along with its associated skills encompasses. Further, as also illustrated above, while some literature sources address skills associated with technology and digital applications in combination, thereby providing no clear demarcation between these skills (see e. g. Daheim & Wintermann, 2016); Ilomäki et al., 2011), others solely address the notion of digital skills when seeking to refer to skills associated with the use and understanding of technology and digital applications (see e. g. Kispeter, 2018; UNESCO, 2018). The aforementioned points underline the above-stated difficulties in identifying a coherent definition that adequately describes the skill category of technological and digital skills, and that, consequently, would have been considered useful and valuable for the purpose of the present thesis. Nevertheless, it still rests in the author's hope that the definitions or descriptions addressing the domain of technological and digital skills presented above provide the reader with a solid idea or understanding about the nature and character of this skill category.

This being said, typical skills within this category include skills associated with working with, understanding, and controlling technologies, technology design and programming, sophisticated data analysis, the development of smart hardware and robotics, blockchain technology development, digital learning skills and digital literacy (Bughin et al., 2018; Daheim & Wintermann, 2016; Kirchherr et al., 2018; WEF, 2018). As noted by Ceemet (2018), digital literacy refers to skills, such as coding and cybersecurity, while digital learning encompasses both the learning of digital skills as well as the utilization of digital technologies.

In view of the above-mentioned points, it should also be noted that, even though technological and digital skills and higher-order cognitive skills are cited as two distinct skill categories as presented in Table 1, some skills associated with the category of technological skills may still require higher-order cognitive skills (Bughin et al., 2018). Moreover, as already indicated above, in terms of the skills that belong to the domain of technological skills, the skill classification proposed by Bughin et al. (2018) counts the category of digital skills towards the main category depicting technological skills. When discussing their workforce skills model, Bughin et al. (2018) argued that the skill category of technological skills encompasses, among others, basic digital skills, mathematical skills, skills associated with technology design and engineering along with skills related to scientific research and development (Bughin et al., 2018). Nevertheless, the future skills framework developed by Kirchherr et al. (2018) provides a differing viewpoint. To be more specific, the framework outlined by Kirchherr et al. (2018) distinguishes between the two main skill categories of technological skills and digital skills. While the present work strongly acknowledges that this issue may be subject to debate, for the purpose of clarity and to avoid confusion, the present work follows the approach pursued by Kirchherr et al. (2018) by distinguishing digital skills from technological skills and by viewing both skill categories as main skill categories. Nevertheless, due to the apparent overlap between the two skill categories in terms of associated skills as evident in the relevant literature reviewed for the purpose of this thesis (see e. g Bughin et al., 2018), it was decided that, within the context of the present thesis, the two skill categories of digital and technological skills are listed as one broad skill category as illustrated in Table 1.

Finally, one last skill category that was included into the skills classification as depicted in Table 1 represents the category of systems skills. As illustrated throughout this chapter, some academic sources (see e. g. Bakhshi et al.; 2017) acknowledge systems skills as a main skill category while addressing the anticipated changes in the skill requirements of jobs within the context of increasingly automated work environments in their works. This skill category encompasses skills associated with system thinking, which relates to skills including judgement and decision-making, systems analysis, and systems evaluation (Bakhshi et al., 2017; O*NET, n. d.). In view of this, while judgment and decision-making involve "considering the relative costs and benefits of potential actions to choose the most appropriate one", systems analysis refers to "determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes" (O*NET, n. d., p. 1). Lastly, systems evaluation is associated with "identifying measures or indicators of system performance and the actions needed to improve or correct performance, relative to the goals of the system" (O*NET, n. d., p. 1). In view of this, according to Bakhshi et al. (2017), the broad category of systems skills encompasses skills that refer to "the ability to recognize, understand and act on interconnections and feedback loops in sociotechnical systems" (Bakhshi et al., 2017, p. 14), while Oliveri (2020) described systems skills as "a mindset to think, communicate and learn about systems to make the full patterns clearer, improve and share the understanding of problems and see how to face them effectively" (Oliveri, 2020, p. 1).

After having provided an overview of the main skill categories along with some of their associated skills or skill sets as illustrated in Table 1, the following discussion will now summarize the anticipated future skill trends within the context of job automation based on the literature findings presented throughout this chapter. First, the discussion will summarize the skill categories that are expected to experience a rise in demand within the near future due to increasingly automated work environments, thereby changing the skill requirements of a given job accordingly. The discussion then continues by summarizing the skill categories that are anticipated to see a decline in their demand within the next few years as a result of automation that, again, are expected to shape the skill requirements of jobs. A short overview of the main future skill trends and demand is provided in Table 2.

Table 2: Anticipated Future Skill Trends and Demand

Decline	Growth
▪ Physical & manual skills ▪ Basic cognitive skills	▪ Technological & digital skills ▪ Advanced cognitive skills ▪ Social & emotional skills ▪ System skills

Sources: AIG (2018); Bakhshi et al. (2017); Bughin et al. (2018); Cedefop (2017); Cedefop, (2018); FYA (2017); Manyika, Lund, Chui et al. (2017); OECD, 2018; Oschinski & Wyonch (2017); Rainie & Anderson (2017); Riad, 2017; Tytler et al. (2019); Vazquez et al. (2019); WEF (2018)

To start with, the literature findings presented above clearly illustrate that the increasing adoption and implementation of modern automation technology into the work environment is expected to effectuate a growth in demand for technological and digital skills (Vazquez et al., 2019; WEF, 2018). With regard to this, the analysis conducted by the WEF (2018) suggests a significant rise in demand for different types of technology competency (WEF, 2018). Further, Bughin et al. (2018) found that both advanced and more basic technological skills, are expected to significantly grow in demand, albeit with varying intensity, as a result of the increasing adoption and implementation of modern automation technology throughout the work environment. In relation to this, STEM skills are also expected to increase in importance within the context of increasingly automated work environments, according to various sources (see e. g. AIG, 2018), as STEM skills are considered to be essential in attaining and improving digital competence (Ceemet, 2018). According to the AIG (2018), as modern automation technologies are further progressing and becoming increasingly complex, skills related to the domain of STEM will increasingly be demanded as an entry level requirement (AIG, 2018).

In addition, the findings obtained from the literature imply that, in general, higher-order or advanced cognitive skills, such as critical and creative thinking skills, are expected to experience an upsurge in demand within the years to come due to automation (Bakhshi et al., 2017; Bughin et al., 2018; Cedefop, 2018; Manyika, Lund, Chui et al., 2017). Nevertheless, the findings obtained by Bughin et al. (2018) suggest that certain skills relating to the main skill category of higher-order cognitive skills may, in fact, maintain a certain stability or even see a decrease in demand by 2030 (Bughin et al., 2018). With regard to the increasing importance of advanced cognitive skills, the literature findings presented above commonly underline the particular importance of skills related to learning (see e. g. Dawson, 2017; Rainie & Anderson, 2017; Tytler et al., 2019). As underlined by Dawson (2017) and Tytler et al. (2019), workers need to possess the ability to learn in order for them to adequately manage and respond to continuous change. Further, according to Tytler et al. (2019), the ability to learn will be essential for workers to succeed in the future labor market as growing emphasis will be placed on lifelong learning to ensure that workers acquire and continue to develop the skills required to thrive in increasingly dynamic and automated work environments (Tytler et al., 2019). This point is also underlined by Rainie and Anderson (2017), who stressed that the skill to continue to learn will be essential in all future jobs (Rainie & Anderson, 2017).

To continue, the discussion provided above also stresses the importance for workers to possess high levels of social and emotional skills including skills related to communication, collaboration, empathy, emotional control, and coordination in order for them to succeed in increasingly automated workplaces (Bughin et al., 2018; Cedefop, 2017; Cedefop, 2018; Manyika, Lund, Chui et al., 2017; Vazquez et al., 2019). In view of this, the literature findings suggest that, in general, skills relating to interpersonal competencies, soft skills, as well as entrepreneurial skills, and thus, social and emotional skills, all are expected to both become increasingly relevant as well as increase in demand within the context of anticipated future work environments increasingly characterized by automation (AIG, 2018; Bakhshi et al., 2017; Bughin et al., 2018; Cedefop, 2017; Oschinski & Wyonch, 2017; Servoz, 2019; Vazquez et al., 2019).

Furthermore, the findings presented throughout this chapter imply that systems skills are also expected to grow in demand due to increasing automation within the context of work environments (Bakhshi et al., 2017; Rainie & Anderson, 2017). Bakhshi et al. (2017), for example, argued that skills associated with system thinking are highly likely to grow in demand within the context of increasingly automated work environments.

Moreover, according to various sources cited throughout this chapter, the combination of distinct skill categories is anticipated to become more and more important within the context of increasingly automated work environments (see e. g. Riad, 2017; Vazquez et al., 2019). Vazquez et al. (2019), for example, argued that the combination of both digital and non-cognitive skills, whereby the latter is also commonly referred to as social & emotional skills, will likely experience a growth in demand within the near future. Further, Riad (2017), for example stressed the importance for workers to hold high levels of both higher-order cognitive skills as well as soft skills. Further, the findings also suggest that, in order to thrive in anticipated future labor markets, workers will need to hold adequate levels of not only meta-cognitive skills and non-cognitive skills, but also sufficient levels of digital skills (OECD, 2018; Vazquez et al., 2019). Moreover, according to the FYA (2017), workers need to be problem-solvers and critical thinkers, they have to be good communicators and engagers, and they need to be educated in science, mathematics, and technology (FYA, 2017). In addition, the findings elaborated above imply that it is essential for future workers to possess high levels of both STEM skills and enterprise skills (FYA, 2017). In relation to the above-mentioned points, the findings presented above also underline the relevance and importance of transferable skills and cross-disciplinary skills (see e. g. Dawson, 2017; Tytler et al., 2019). Further, the aforementioned point also stresses the anticipated increase in the demand for workers to hold a diverse portfolio of skills that enable workers to utilize their skill sets across a range of disciplines. All in all, the findings clearly emphasize the importance for workers to possess a diverse set of distinct skills in order to succeed and thrive in increasingly automated work environments (Bughin et al., 2018; FYA, 2017; OECD, 2018; Vazquez et al., 2019).

After providing a summary in terms of the skill categories expected to grow in demand within the near future due to increasing automation, the following discussion will now focus on those skill categories that are anticipated to experience a decline in demand as a result of the progressive adoption and implementation of modern automation technology into the work environment.

To begin with, based on various literature sources reviewed for the purpose of the literature review conducted in the realm of this work, it is expected that psychomotor, manual, and physical skills will likely experience a decline in demand (see e. g. Bakhshi et al., 2017; Manyika, Lund, Chui et al., 2017; WEF, 2018). However, in spite of the anticipated decline in demand for those skills, this skill category is nevertheless expected to remain a significant element of the future workplace (Bughin et al., 2018). Further, findings suggest that this overall downward trend concerning the need for physical and manual skills is not expected to be visible across all sectors (Bughin et al., 2018). However, it needs to be stressed again at this point that potential sectoral differences in terms of anticipated skill trends and demand are not the focus of the present work due to the limited scope of the present thesis, and that the focus lies solely on the general trends and changes in terms of the skill requirements of jobs as identified from extant literature reviewed for the sake of the literature review conducted in the realm of this work. Nevertheless, the literature findings that suggest sectoral differences with regard to anticipated changes in the skill requirements of jobs, may, nevertheless, constitute noteworthy insights for possible future research endeavors as will be more thoroughly discussed later in this work.

Further, the literature findings presented above imply that basic cognitive skills are likely to decrease in demand within the next few years due to the increasing capacity and proficiency of certain automation technologies (Bughin et al., 2018). In view of this and according to Bughin et al. (2018), the anticipated demand for cognitive skills is expected to shift from basic towards higher cognitive skills.

In view of the findings presented above, it is anticipated that both physical skills as well as basic cognitive skills alone won't be sufficient in order for workers to succeed in the future labor market as modern automation technologies are expected to increasingly perform work tasks that mainly require these kinds of skills (Bughin et al., 2018). Further, the literature findings presented above generally highlight a growing demand for higher-order and uniquely human skills, such as skills relating to advanced cognitive skills, social and emotional skills, as well as systems skills, along with an increase in demand for technological and digital skills in the face of increasingly automated work environments (see e. g. Bughin et al., 2018; Dawson, 2017; Rainie & Anderson, 2017; Tytler et al., 2019; WEF, 2018). Further, the findings suggest that obtaining and developing a diverse portfolio of distinct skills pertaining to the various skill categories that are expected to increase in demand within the near future as a result of automation will be especially important for workers to thrive in the anticipated future world of work. Overall, with regard to the findings presented above that suggest that uniquely human skills are expected to play an ever greater role in terms of future skill needs and demand, the literature findings generally illustrate and emphasize that, as a result of increasingly automated work environments, inherently human skills including creativity, critical thinking, communication, teamworking, and negotiation will become ever more relevant and important (Dawson, 2017; Rainie & Anderson, 2017; Tytler et al., 2019; WEF, 2018). With regard to this, Rainie and Anderson (2017) stressed the increasing importance of uniquely human skills as even modern, sophisticated automation technologies have difficulties to replicate or emulate such skills including emotional intelligence, empathy, human meta communication, and creativity effectively and adequately. With regard to this, Dawson (2017) stressed that workers will need to increasingly shift their emphasis to uniquely human skills that differentiate them from modern automation technology, such as creativity, imagination, emotional intelligence, and empathy (Dawson, 2017).

Having provided an overview of the main skill trends and changes that are anticipated to emerge and unfold within the coming years as a result of increasingly automated work environments, the subsequent chapter will continue by outlining and presenting the qualitative research study conducted in the realm of the present thesis for the purpose of complementing and enriching the findings and insights derived by means of the extensive literature review presented above.

3 Empirical Study

3.1 Research Design: Qualitative Research Study

For the purpose of providing a thorough and coherent answer to the central research question of the present thesis, a qualitative research design was chosen. In view of this, the following discussion will provide a short overview of qualitative research along with arguments that justify the utilization of a qualitative research approach in the context of the present study in order to generate a coherent answer to the research question asked in the context of the present thesis.

According to Hennink et al. (2020), qualitative research presents a research approach "that allows you to examine people's experiences in detail" (Hennink et al., 2020, p. 10) by utilizing specifically chosen research methods, such as in-depth interviews. More specifically, the qualitative research approach is based on a constructivist epistemology (Yilmaz, 2013) and enables the researcher to identify issues based on the point of view of the study participants as well as to develop an understanding of meaning and interpretations that the participants attribute to certain behavior, events, or objects (Hennink et al., 2020). In relation to this, King and Brooks (2016) argued that the fundamental concern of qualitative research rests on the perspective of viewing human beings as meaning-makers. This predominant focus of qualitative research on the human experience of individuals allows researchers to obtain a deeper understanding of the social world, in which the respective individuals reside in (King & Brooks, 2016). Further, qualitative research approaches, which generally seek to explore the experience and understanding of the social world, are commonly based on interpretivism (King & Brooks, 2016). Thus, researchers that are adopting a qualitative research approach seek to "make sense of, or interpret, phenomena in terms of the meanings people bring to them" (Denzin & Lincoln, 2008, p. 4). In view of this, the interpretive paradigm recognizes that an individual's perception and experience of reality are subjective, which, in turn, means that there can exist a variety of perspectives on reality (Hennink et al., 2020). With regard to this, interpretivism emphasizes the innate subjectivity of not only the participants of the study, but also the subjectivity of the researcher, thereby also recognizing that a researcher's background and values may have a certain affect or impact on creating research data (Hennink et al., 2020). Further, as researchers aim to provide interpretations to the meanings that are attributed by the study participants to their individual viewpoints and experiences, interpretivism is also an integral part of qualitative data analysis (Hennink et al., 2020). Moreover, qualitative research approaches typically seek to answer *what*, *how*, and *why* questions and acknowledge that "events, cases, processes, situations, individuals and their behaviors are unique, context-dependent and largely non-generalizable" (Yilmaz, 2013, p. 317). Further, due to the in-depth character of qualitative research, only few study participants are required as the purpose of qualitative research is to obtain in-depth information as opposed to statistical representativeness (Hennink et al., 2020). In view of the aforementioned points, and as the objective of the study was to obtain a more in-depth understanding about how the skill requirements of jobs are expected to change within the context of increasingly automated work environments on the basis of the viewpoints and experiences of chosen individuals, a qualitative research approach seemed to be an appropriate and valuable choice in order to explore an individual's belief and viewpoint concerning the matter at hand and to obtain and in-depth understanding of the anticipated skill trends and changes as a result of automation.

3.2 Data Collection

The central purpose of the present thesis along with the present empirical study is to generate valuable and rich insights and viewpoints regarding the central research topic of the present work. Thus, in order to complement and enrich the findings derived by means of the extensive literature review carried out prior to conducting the study, expert interviews were chosen as the most suitable approach to yield additional findings and insights with regard to the question of how job automation is changing the skill requirements of jobs. As argued by Harrell and Bradley (2009), interviews may be utilized as a primary data gathering tool in order to yield information about an individual's experiences, beliefs, or viewpoints, as well as to access an individual's expert knowledge. Further, as noted by Palmer and Bolderston (2006), utilizing interviews for the data collection process provides the opportunity of not only obtaining an insight into the subjective world of the interview participant, but also to develop a more in-depth understanding of the nature or meaning of the individual's subjective and everyday experiences. In view of the aforementioned points and within the realm of the qualitative research study, eight in-depth semi-structured interviews with experts and professionals with diverse disciplinary backgrounds and research interests for the purpose of obtaining various perspectives, views, and experiences on anticipated future skill trends and changes within the context of increasingly automated work environments were conducted in German or English language. Due to their perceived knowledge and experience regarding this research topic, all of the experts interviewed in the realm of the qualitative research study were attributed the required authority and quality to make informed remarks and predictions about this subject field. Table 3 depicts the full list of experts interviewed in the realm of the qualitative research study along with a short description of their profiles and interview information.

Table 3: Study Participants

Interview Participant	Gender	Date of Interview	Length of Interview	Type of Organization	Professional Background (Example)
1	male	26.10.2020	03:18:52 (Breaks/Disruptions included)	Focus on digital innovation, consulting, and transformation	Digital transformation, global organization change management
2	male	27.10.2020	00:40:26	Multi-national professional services company	Lead Solution Architect for Artificial

					Intelligence in DACH/ASG; Senior Principal for Digital Solution Design
3	male	27.10.2020	01:43:45	Multi-national professional services company	Information Technology, Computer Science
4	male	30.10.2020	00:49:20	Business consulting	HR, Business, and (IT) Management consulting, Project Management,
5	female	04.11.2020	00:30:46	Multi-national professional services company	Innovation and Thought Leadership Principal, Artificial Intelligence
6	female	09.11.2020	00:31:31	Automation company	Project Manager, Principal Technical Writer
7	female	10.11.2020	00:19:12	Financial Services Company	Project Manager, People Development expert
8	male	13.11.2020	00:27:33	Business consulting	Consulting and Business Process Services; complex international transformations; HR Consulting

In view of this, it needs to be emphasized at this point that, in the face of maintaining the anonymity of the interview participants, it was refrained from providing a detailed profile description of the interviewees. Nevertheless, it may be noted at this point that, due to the diverse fields of interests, experiences, and professional backgrounds of the interviewees, a valuable degree of heterogeneity could be acquired that, as will be thoroughly discussed later, beneficially contributed to obtaining diverse and in-depth insights with regard to the central research question asked within the context of the present thesis. Moreover, all potential interview partners were initially contacted via email. As already stressed earlier, the prerequisite to qualify as a study participant was to have a strong understanding of the potential impact of automation on the future work, jobs, and skills landscape in order to make valuable contributions and share relevant insights that contribute to answering the central research question of the present thesis.

This being said, a semi-structured interview style was deployed when conducting the interviews with the experts as already mentioned above. In view of this, semi-structured interviews are generally based on an interview guide that entails questions and topics deemed important to answer the respective research question, while still allowing the researcher to exert a certain amount of freedom and discretion during the interview process by, for example, changing the order of the questions and providing probes in order to obtain additional or more in-depth information and insights (Harrell & Bradley, 2009). Consistent with this, King and Brooks (2016) noted that a semi-structured interview format allows the researcher to conduct the interview on the basis of an interview guideline that emphasizes all areas and topics the researcher seeks to address and generally guides the interview process, while, at the same time, ensures that sufficient flexibility is given that provides the interviewers with the opportunity to actively steer the conversation in directions that may be relevant for them. Overall, semi-structured interviews present a valuable data collection method when the researcher seeks to obtain an in-depth understanding about a certain topic as well as of the responses provided by the interview participants (Harrell & Bradley, 2009). Further, as noted by King (2004a), the objective of any qualitative research interview is to explore the central research topic from the interviewee's perspective, thereby apprehending how and why the interviewee holds a specific viewpoint. Moreover, a central element of the qualitative research interview technique presents the "nature of the relationship between interviewer and interviewee" (King, 2004a, p. 11). In light of this, King (2004a) stressed that the interviewee is viewed as a participant of the research study, who may actively influence the interview process instead of merely passively replying or reacting to the questions asked by the interviewer. Further, as already noted earlier, the findings derived from the literature review conducted in the realm of this thesis constituted the discussion and knowledge base of the expert interviews. In view of this, as already indicated earlier, the objective of the expert interviews was to obtain additional insights and to gain a deeper understanding of how job automation is changing the skill requirements of jobs across advanced economies.

Moreover, in terms of the interview execution, each interview participant was assured of confidentiality and informed about the purpose and objective of the interview prior to the start of the interview. Further, permission to record the interviews for subsequent transcription was obtained from each participant in the beginning of each interview. In addition, for the purpose of executing the interviews in a well-organized and clear manner, an interview guideline was developed that encompassed the main interview questions and outlined the most important steps and topics that needed to be acknowledged and addressed during the interview process. The full interview guideline can be found in Appendix A. With regard to this, as the interviews were conducted in both English and German language, depending on the personal background and priority of the interviewees, Appendix A enlists the interview guideline in both English and German language. Further, as already noted earlier, the insights and findings derived from the literature review conducted in the realm of this thesis served as a knowledge base for the design of the interview questions. Hence, the interview guideline utilized for carrying out the interviews was designed based on the core trends and insights that were identified by means of the literature review conducted earlier. Nevertheless, it is important to stress at this point that the interview guideline merely served as a guide to follow during the interviews in order to ensure that the most important topics would be addressed. As remarked by King (2004a), flexibility presents the most essential factor in conducting qualitative interviews successfully. Thus, for the purpose of maintaining a high level of flexibility during the interview process, the initial interview questions were modified throughout the course of the respective interview according to the professional background and knowledge fields of the respective interview partner.

Moreover, in terms of the timeline and length of the interviews, the interviews were conducted between the 26th of October and the 13th of November 2020 and lasted between 00:19:12 and 03:18:52 hours, whereby the interview with the longest duration entailed several breaks and disruptions that need to be acknowledged at this point. Further, due to the travel restrictions and safety requirements posed by the Covid-19 pandemic, all interviews were conducted either online via the online meeting and conference platform Zoom or via telephone. In addition, all of the interviews were recorded after having obtained the consent of the interviewees. Furthermore, each interview carried out was transcribed in order to subsequently analyze the textual data gathered through the transcription of the interviews. Concerning the transcription process, the interviews were transcribed by utilizing both a summarized transcription style as well as a verbatim transcription style. The summarized transcription format was employed for those segments of the audio or video data that were deemed not relevant for answering the central research question of the present thesis. Conversely, the verbatim transcription format was used for those data segments that were considered as being particularly relevant for providing a precise and coherent answer to the research question at hand. With regard to the analysis of the collected data, the subsequent section will outline the data analysis process conducted in the realm of the present study in more detail.

3.3 Data Analysis

The following discussion will outline the approach followed and applied to analyze and process the data collected by means of the semi-structured expert interviews conducted in the context of the present qualitative research study. For the purpose of processing and analyzing the qualitative data obtained through the expert interviews, a thematic analysis approach in the form of template analysis was chosen (see e. g. King & Brooks, 2016). As noted by King and Brooks (2016), "thematic analysis refers to a broad approach to organizing and interpreting qualitative data" (King & Brooks, 2016, p. 4), whereby many varying forms and styles exist. In view of this, Brooks et al. (2015) noted that template analysis presents a specific style of thematic analysis. In general, all forms or types of thematic analysis encompass two interconnected key processes (King & Brooks, 2016). The first process involves the definition of themes that characterize relevant and important aspects of the data that is analyzed, while the second process includes the organization of the defined themes into a certain structure, which reflects the different relationships between the distinct themes (King & Brooks, 2016).

In view of the aforementioned points, Brooks et al. (2015) argued that, while thematic analysis presents "a broad category of approaches to qualitative analysis that seek to define themes within data and organize those themes into some type of structure to aid interpretation" (Brooks et al., 2015, p. 206), "template analysis is a form of thematic analysis which emphasizes the use of hierarchical coding but balances a relatively high degree of structure in the process of analyzing textual data with the flexibility to adapt it to the needs of a particular study" (Brooks et al., 2015, p. 203). As stressed by Brooks et al. (2015), the flexibility integral to template analysis enables this technique to be adjusted to the particular demands of a specific study and to the specific study's philosophical stance.

In general, among other kinds of textual data, template analysis is utilized for the analysis of textual data in the form of interview transcripts (Brooks & King, 2014). In view of this, a central characteristic of template analysis presents its use of a priori themes, which enables researchers to determine certain themes prior to the analysis process (Brooks et al., 2015). Generally speaking, themes refer to "recurrent features of participants' accounts characterizing particular perceptions and/or experiences that the researcher sees as relevant to their research question" (Brooks & King, 2014, p. 4). In relation to this, a priori themes are commonly defined as themes that are "identified in advance of coding" (King & Brooks, 2016, p. 28). In view of this, a priori themes refer to themes that represent those issues, matters, or areas that are determined as being especially significant and relevant to the overall objective of a given research project and are often expressed as key thematic areas within the interview guideline (King et al., 2002). While Brooks et al. (2015) remarked that the usage of a priori themes may allow for increased emphasis on key areas that may be particularly relevant to a specific study, King (2004b) noted that the definition of a priori codes typically assists in guiding the overall analysis. However, it needs to be emphasized that a priori themes are always tentative or provisional, and therefore may be changed, redefined or adapted throughout the course of the analysis procedure, depending on whether they reveal themselves to be useful, relevant, and valuable to the analysis at hand or not (Brooks et al., 2015). Overall, throughout the data analysis process, the initially defined a priori themes need to remain open to changes, such as modification or deletion, whilst the coding template is being developed and refined from its preliminary structure towards its advanced and final form (King et al., 2002).

Further, according to King (2004b), the essence of template analysis constitutes the development of a list of codes that depicts the distinct themes that were identified in the textual data. Hence, one core feature of doing template analysis is the creation of a coding template that captures all themes evident in a given data set, which the researcher identified as relevant and important to the study's objective or purpose, and that structures the identified themes in a valuable and meaningful way (Brooks & King, 2014; Brooks et al., 2015). Generally speaking, the concept of a *code* refers to "a label attached to a section of text to index it as relating to a theme or issue in the data which the researcher has identified as important to his or her interpretation" (King, 2004b, p. 257), while the term *coding* refers to "the process of identifying themes in accounts and attaching labels (codes) to index them" (Brooks & King, 2014, p. 4). As argued by King (2004b), the coding template is structured in a manner which reflects the different relationships between the distinct themes as identified by the researcher and is usually organized in a hierarchical structure. In order to structure the different codes hierarchically, different codes that are similar to each other are grouped together to generate more general or broad so-called higher-order codes (King, 2004b). In view of this, while the more precisely defined so-called lower order codes enable a more detailed differentiation of the issues, matters or experiences covered by the interviews, the more general or broader defined higher-order codes typically serve to provide a clear overview of the overall direction that the respective interview steered to (King, 2004b). All in all, the hierarchical organization of codes enables the researcher to analyze textual data, such as interview transcripts, at differing levels of specificity (King, 2004b). In relation the aforementioned points, King and Brooks (2016) noted that the notions *theme* and *code* are often used interchangeably in template analysis.

All in all, due to its allowance of the use of a priori themes, along with its structured, but still flexible and adaptable approach to data analysis, as well as its usefulness for analyzing interview transcripts, template analysis seemed as an adequate and appropriate technique for processing and analyzing the full textual data set obtained by means of the expert interviews conducted in the realm of the present study.

In view of the aforementioned points, the remainder of this section will outline the steps that were conducted by the researcher in order to process and analyze the full textual data set encompassing the eight interview transcripts developed in the realm of this study. The approach and the steps taken for analyzing and processing the textual data in form of the interview transcripts largely followed the template analysis technique proposed by Brooks et al. (2015), Brooks and King (2014), King (2004b), King and Brooks (2016), and King et al. (2002). In view of this, the following discussion will outline the seven steps usually involved in doing template analysis as proposed by King and Brooks (2016) that were conducted in order to process and analyze the textual data set in form of the eight interview transcripts obtained from the expert interviews conducted in the realm of the present study. However, it needs to be noted at this point that the fifth and sixth step in doing template analysis as outlined by King and Brooks (2016) will be presented as one broad step in the subsequent discussion. In view of the aforementioned points, it is also worth mentioning at this point that, while the adherence of the seven steps involved in template analysis as proposed by King and Brooks (2016) proved to be a valuable technique in order to maintaining a clear structure with regards to the data analysis process undertaken in the realm of the present study, it is nevertheless important to emphasize that, within the course of the data analysis process described below, the seven procedural steps characteristic of template analysis were occasionally repeated throughout the data analysis process. In relation to this, King and Brooks (2016) stressed that, in practice, analyzing data in an iterative manner is common to carrying out template analysis, whereby the researcher typically moves back and forth between the different steps involved in template analysis before completing the analysis of a given data set.

Familiarization with the data

To begin with, as a very first step and in accordance with the seven steps outlined by King and Brooks (2016), a thorough familiarization with the data took place as, in general, a high-level of familiarization with the data that needs to be processed and analyzed usually translates into a high-quality data analysis process (King & Brooks, 2016). In view of this, the transcription of the expert interviews already served as a valuable method to become familiar with the full textual data set in form of the eight interview transcripts as this transcription process allowed for deeper engagement and reflection in terms of the respective data. In addition, the audio or video recordings of the interviews were listened to, when deemed necessary, multiple times and the interview transcripts were reviewed several times, as well.

Preliminary coding

As a next and second step, preliminary coding of a subset of the textual data in the form of the interview transcripts was conducted. As already indicated earlier, in template analysis it is perfectly acceptable to begin with so-called a priori themes that are defined in advance as potentially being relevant and valuable to the analysis, but are always provisional and tentative and, thus, may be altered and adapted in the course of the analysis (Brooks et al., 2015). As remarked by King and Brooks (2016), the identification of a priori themes may assist the researcher in focusing on specific issues or aspects regarding the central study topic and may be valuable to utilize when the significance of a certain issue or aspect with respect to the central research question of a given study project is already firmly determined. In the context of the present study, the a priori themes in the form of codes were defined on the basis of the key literature findings presented earlier in this work. Thus, the a priori themes used in the realm of the data analysis procedure encompassed the key themes identified by means of the extensive literature review conducted as part of the present thesis. Further, the coding process was undertaken with the assistance of the qualitative research software MAXQDA 2020. In view of this, at the preliminary coding stage, anything in the data that seemed interesting, important, and relevant to answering the central research question of the present thesis and which was considered to underpin the a priori themes developed prior to this stage was highlighted.

Clustering

Next, based on the preliminary coding process conducted earlier, both the a priori themes as well as newly emerging themes were clustered into groups and were arranged into a hierarchical order. As already indicated earlier, within the context of doing template analysis, emphasis is put on a hierarchical coding technique, where broad, general themes typically comprise more detailed and more specific themes (Brooks & King, 2014). In view of this and in the context of the present study, the hierarchical coding process allowed for an analysis of the textual data in form of the eight interview transcripts at varying levels of specificity.

Producing an initial template

This clustering of themes constituted the basis for developing an initial coding template. Hence, in accordance with the fourth step of carrying out template analysis as proposed by Brooks et al. (2015) and King and Brooks (2016), an initial coding template was designed on the basis of a partial amount of the full textual data set in form of the interview transcripts. As noted by Brooks and King (2014), the initial coding template is structured in a way, which valuably and meaningfully depicts the various relationships between the distinct codes or themes (Brooks & King, 2014). Further, according to Brooks & King (2014), while it is well-accepted in template analysis to design the initial version of the coding template on the basis of only a subset of the entire data, the researcher needs to make sure that the subset of the data chosen for designing the initial template encompasses a selection of diverse accounts that cover an appropriate mixture or assembly of the overall themes, matters, or experiences evident in the entire data set (Brooks & King, 2014). In the context of the present thesis, given that the researcher already had a number of well-defined a priori themes in her mind in the beginning of the preliminary coding process as already indicated above, an initial version of the coding template was produced after having analyzed four interview transcripts. As argued by Brooks et al. (2015), the specific point at which it seems adequate to develop the initial version of the coding template differs between study projects and thus, cannot be specified beforehand. Rather, once the researcher is confident that the subset of the data chosen reflects an appropriate cross-section of the themes, matters, and experiences that are evident in the entire data set, an initial version of the coding template may be designed (Brooks et al., 2015). In view of this and within the context of the present study, at the point where no more markedly different new themes were identified in the preliminary coding process, an initial version of the coding template was developed. With regard to the development of the initial coding template in the context of the present study, the usage of the a priori themes that were defined in advance on the basis of the relevant literature findings presented earlier in this work also assisted in designing the initial coding template. In addition, with regard to the aforementioned point, the interview guideline developed for the purpose of guiding the expert interviews conducted in the realm of the present study further contributed to the development of the initial version of the coding template. As argued by King (2004b), the questions, probes, and issues addressed in the interview guideline commonly present a useful starting point for developing an initial coding template. In the case of the present study, the main questions listed in the interview guideline used to carry out the eight expert interviews were all derived from the literature findings obtained by means of the extensive literature review carried out prior to the execution of the empirical study at hand. In view of this and in terms of developing the initial coding template, some of the main questions included in the interview guideline that specifically related to potential future skill trends and changes in the context of automation therefore served as so-called higher-order codes, while certain secondary or subsequent questions and probes relating to each broad interview topic as presented in the interview guideline initially served as potential lower-order codes.

Developing and applying the final coding template

Following the creation of an initial version of a coding template, the researcher then needs to continue with the analysis of the full data set in a systematic manner, thereby identifying those text segments that seem relevant and significant to answering the central research question of a study project and also labelling the respective segments with adequate codes listed in the initial coding template (King, 2004b). Thus, once the researcher has developed an initial coding template, this initial coding template needs then to be applied to the remaining data set (King & Brooks, 2016). During this process, imperfections or insufficiencies regarding the initial coding template may be identified, which, in turn, necessitates the implementation of various changes on the initial template (King, 2004b). As noted by Brooks and King (2014), the application of the initial version of the coding template to the full data set may necessitate the modification of the coding template by, for example, integrating new themes, adjusting existing themes, as well as deleting those themes that are rendered not appropriate anymore. With regard to this, in the context of the present study, after having developed the initial coding template on the basis of four interview transcripts, the initial version of the coding template was then applied to the full textual data set and was adapted and modified when necessary.

In terms of the present study, once it seemed that the coding template adequately and sufficiently captured all relevant issues, matters, and experiences that were evident in the full textual data set comprising all eight interview transcripts, a final version of the coding template was defined. All in all, the discipline of developing a comprehensive coding template within the context of doing template analysis generally pushes the researcher towards following a well-organized and coherent approach to analyzing a given data set, which, in turn, may be of great assistance when seeking to generate a clear, well-structured, and concise account of a specific study project (King, 2004b). The final coding template presented in a linear format and based on a hierarchical coding structure can be found in the Appendix. As illustrated, the final coding template developed in the realm of the data analysis process using template analysis entails a hierarchical structure whereby the highest-level codes illustrate the broader, general themes identified in the coding process, while the lower-level codes represent the more detailed and narrowly defined themes within the broader defined themes. In view of this, the final version of the coding template generated in the context of the present study depicts all of the themes identified by means of the coding process. Finally, as argued by King and Brooks (2016), once a final coding template is designed, this may then serve as both the basis for interpreting the respective data and as a valuable guide with respect to presenting the study's findings.

Writing up

In view of the aforementioned points, as stressed by King and Brooks (2016), the successful development of a final coding template does not signal the end of conducting template analysis within the context of a qualitative research design. With regard to this, the authors noted that, as a subsequent task, the researcher then needs to both establish a conclusive interpretation of the data analyzed as well as present the overall findings (King & Brooks, 2016). Hence, when having completed the analytical process, it is then required of the researcher to present the findings in a written and coherent manner (King & Brooks, 2016). Thus, in light of the points mentioned above, the following section will continue by providing a thorough and clear account of the findings obtained by means of the present study using the template analysis technique.

3.4 Empirical Findings

All in all, the expert interviews carried out as part of the present empirical study produced very data-rich and valuable accounts of the interview participants' perspectives, opinions, and viewpoints regarding the central research question of the present work. Hence, the data collection in the form of expert interviews yielded a number of valuable insights and findings concerning future skill trends, changes, and demand in the context of increasingly automated work environments that will be presented in the present section. Overall, the analysis of the interview data using the template analysis approach identified a number of dominant themes regarding the central research topic of this thesis. In view of this, the following discussion will outline the findings derived from the interview study. For the purpose of generating a clear and concise thematic discussion, the findings will be presented according to the main themes identified by means of the data analysis process using the template analysis technique as elaborated in the previous section. As argued by King and Brooks (2016), structuring the presentation of a study's findings according to the main themes identified not only presents an efficient method to provide a cohesive account of the findings, but also allows for emphasizing the key themes that the discussion seeks to focus on. Further, direct quotes of the interview participants will be provided when relevant as they not only represent and substantiate the interpretation of the data, but also enable readers to develop their own appraisal with regard to the credibility of the presented findings (Brooks & King, 2014). The direct quotes provided will be marked with double quotation marks to illustrate that the respective quotes do not refer to the wording used by the researcher, but instead to the wording used by the interview participants.

3.4.1 Effects of Job Automation

To begin with, all interview respondents stated that they expect that automation will be having substantial effects on jobs. More specifically, the findings suggest that the adoption and implementation of modern automation technologies into the workplace will not only cause the displacement and decline as well as the creation and growth of certain jobs and work tasks but will also effectuate substantial changes in already existing jobs, thereby causing significant job transformation. In fact, according to the experts, while job automation is already having, at this point, large effects on jobs, ongoing and continuous technological advances and change will effectuate even wider changes to jobs in general. For example, one manager of a consulting firm stated that, at this point in time, the degree of maturity of automation resides still at the very beginning and that, with increasing capabilities of automation technology, the range of work tasks and work activities that could be automated also increases. This point was also underlined by another respondent, who argued that, due to ongoing research, current automation technologies will become increasingly advanced, which, in turn, also has substantial effects on jobs.

Consequently, as argued by one interviewee, automation may not only affect the routine and repetitive jobs or work tasks but may also invade other types of jobs. In relation to this, one interview respondent referred to one quote he once read that states that "in the short run, the effects of these technologies are overestimated […] in the long run, they are underestimated" (Interviewee 3). Thus, on the one hand, the respondent noted that there often seems to be a certain hype explosion surrounding the introduction or invention of new technologies where people would expect wide-scale disruption brought about by new technologies, but that the real effects of these rarely live up to those expectations as "it will take longer for some of these technologies to really be adopted" (Interviewee 3). One the other hand, according to the respondent, the long-term effects may indeed be very disruptive and that one should not underestimate the effects of certain technologies that may occur in the long run. With regard to the last point, the respondent stressed that ongoing technological advances in the domain of artificial intelligence, machine-learning and deep learning may result in the large-scale disruption of many white-collar jobs that hitherto were relative secure from automation.

Job decline and job destruction

In terms of the job displacement effect of automation, several interview respondents stressed that they expect that automation will displace or eliminate certain job roles. For example, one respondent argued that "there are certain job roles that will be clearly displaced by automation technologies"[1] (Interviewee 2). The interviewee then provided an example of an insurance company, in which all the job roles that were based on the sorting of incoming mail were displaced by automation. In terms of the displacement effect of automation, another respondent stressed that "every job role or task that do not require, to a large extent, inherently human skills will be displaced by automation as humans are not needed anymore to perform this type of jobs or work tasks"[2] (Interviewee 8). Further, with regard to a more generalized view, one

[1] Original German statement: „Es gibt gewisse Job-Rollen, die eindeutig von der Technologie verdrängt werden."

[2] Original German statement: „[…], weil alles, was nicht tief ausgeprägt ist an menschlichen Skills, wird von der Maschine ersetzt werden, da brauchen wir die Menschen nicht mehr für."

respondent argued that all those people, who do not really add value through their job roles and where automation technologies, such as machine learning, have the necessary capabilities to do this respective job role, are at risk of “having their job rationalized away” (Interviewee 3). In terms of the effects of automation on jobs, another respondent argued that, due to the automation of certain work tasks in a given job role, the respective workers need to shift to other tasks. As stated by the respondent, “roles will change […], some of them will go away completely, […] that’s why we will need to reskill them [the workers] und upskill them […], prepare them for these new roles and new jobs” (Interviewee 7). The findings regarding the changes of job roles due to automation will be further presented shortly within the context of the job transformation effects of automation.

Job transformation and augmentation

In terms of the transformation or reshaping of jobs, several respondents stated that the automation of certain work tasks or activities of a given job does not necessarily result in making the affected workers redundant, but rather effectuates the augmentation of the respective worker’s job role, while still stressing that the affected jobs are undergoing substantial changes due to automation. For example, one respondent argued that, while robotic process automation may take over the rather simple and mindless work tasks, this then enables workers in the respective job role to carry out the more valuable work tasks, such as performing so-called special or exceptional job activities that the machine is not able to perform. According to the interviewee, this has important implications for future skill trends, which will be discussed in more detail shortly.

Consistent with the aforementioned points, another respondent argued that, within many job roles, job automation, or, more specifically, task automation is effectuating a shift in terms of the work tasks that will be carried out by the human workers. In order to illustrate this point, the respondent provided the example of call-center workers. According to the respondent, the adoption and implementation of automation technologies including chatbots, voice bots, and other automation systems that have the ability to handle inquiries are substantially changing the job roles of call-center agents in the sense that the workers shift their focus exclusively on carrying out the more complex work activities that may, for example, relate to so-called escalation cases. As a result, it will be, on the one hand, much more demanded from workers. According to the respondent, these changes also have important implications for the skill requirements of the affected jobs, as will be further outlined shortly. On the other hand, however, workers will not have to perform the rather routine and mindless work tasks anymore as those will become automated. Interestingly, within this context, the respondent also noted that the effects of automation may not always result in workers shifting to the more complex and valuable work tasks as mentioned above. In the expert's view, the usage of automation technologies may also support low-skill workers in, for example, customer service jobs. As remarked by the respondent, the capabilities of the respective automation technologies are sufficiently advanced so that basically any worker, even the low-skilled ones, are able to perform the respective job role. This being said, in reference to the augmentation and job transformation effect of automation, the same respondent also provided the example of factories by stating that "the trend clearly points towards so-called human-plus-machine collaboration, which means that industrial robots increasingly work together with humans, which, in turn, results in substantial changes in the affected job roles"[3] (Interviewee 2). Further, in terms of the augmentation effect of automation, another respondent argued that, in general, having automation technologies taking over the drudge and boring work will make us as workers much more efficient and productive. As stated by the respondent, "I think that is the way technology is going to work […], that [it] would make us so much more productive because we don't have to deal with all of the details anymore" (Interviewee 3). Further, in relation to the aforementioned points, one respondent provided an interesting example concerning the potential benefits of the usage of robots within the context of the coronavirus crisis and noted that this sort of integration of automation into the work environment is likely to increase in the future. According to the respondent, "the corona situation is a new challenge for a lot of professions that need to work with, for example, patients […], patients that are in the quarantine station cannot be touched […], you cannot go there […], now you have robots that may check if everything is good with their health parameters, that everything is good with their temperature […], with a lot of categories that you need to check but that you cannot do in this particular moment, […so] we [will] experience some integration in this sort of professions that need to deal with customers […], so I think we can have [a] more customized integration […], machines need to be more flexible and need to offer more customized solutions, especially now that people have a new sort of needs […], we need to come up with new solutions […] and we probably need machines that will help us in that" (Interviewee 6).

[3] Original German statement: „Aber momentan geht der Trend sehr, sehr stark zu diesen Human-Plus-Machine. Also Industrieroboter, die mit Menschen zusammenarbeiten können […] und das wird natürlich dann wiederum die Arbeit […] verändern."

In terms of the augmentation effect of automation, another respondent argued that not only can automation take over certain work tasks that are rather drudge and boring in nature, leaving the worker with the possibility to spend more time on doing value-adding work, but it can also assist the worker in doing a specific work task. In this context, the respondent provided the example of people using their hands in order to manipulate a robot arm that's, for instance, in a nuclear reactor performing some kind of work. Thus, in relation to the points mentioned above, the same respondent argued that the alarmist idea of a large number of people losing their jobs due to automation has given way to the idea that "there will be collaboration between humans and machines" (Interviewee 3). In view of this, Interviewee 3 further stated that he is pretty certain that, in the future, workers will be increasingly working with machines instead of simply being replaced by them. This point is also underlined by another respondent, who argued that "we are in a new era of automation […], we will have new sort of machines that will be able to collaborate more closely with humans, with the employees" (Interviewee 6). Nevertheless, according to Interviewee 3, even though the augmentation effect may be larger than the displacement effect of workers, the jobs affected are still at high risk of being substantially redefined, which, in turn, also has important implications for the increasing relevance of certain kind of skills, such as technological and digital skills. The specific findings relating to future skill trends, changes, and demand in the context of automation will be further discussed shortly. In terms of the redefinition of jobs, the respondent also argued that, due to the augmentation potential of automation technologies, workers will be much more efficient in performing their jobs or work activities. However, this, in turn, implies, according to the interviewee, that less workers are needed when automation is taking over certain job tasks, thereby, as already argued, making the workers in the respective job role much more efficient and productive. Hence, as stressed by the respondent, the respective job is also redefined in a way that less people are needed for the given job role. This point was also underlined by another interviewee, who argued that "it is reasonable to say that in a factory, in which robots are taking over the majority of tasks, less workers are needed compared to a factory, in which mostly humans work"[4] (Interviewee 2). Thus, according to one respondent, those workers that will be made redundant, will then need to be retrained in different skills that enable them to perform a different kind of job in order to protect them from being let go.

[4] Original German statement: „Eine vollkommen durchrobotisierte co-working Fabrik braucht […] weniger menschliche Arbeitskräfte als eine, [in der] das alles die Menschen machen, klar."

Job growth and job creation

With regard to the job creation or job growth effect of automation, several respondents argued that, within the coming years, they expect that job roles that are directly related to new automation technologies, such as software developers or scientists, will experience an increase in demand. In addition, another expert mentioned the domain of responsible usage of automation technologies, such as artificial intelligence, machine learning, and deep learning, while arguing that, with the growing usage of such technologies, for example the usage for predictive policing purposes, there will be the need for "people [that] look at the responsible use of some of these information processing technologies" (Interviewee 3). In relation to this, another respondent also argued that, besides an increasing need for data scientists, programmers, and artificial intelligence specialists, there is and continues to be the need for people, who are not only able to monitor and supervise such automation technologies, but that are also sufficiently skilled in adequately understanding how the technology works as well as in detecting or identifying any errors the technology may entail. Further, in terms of the question concerning possible future jobs that may be created as a result of increasing automation, another respondent argued that, while it is rather impossible to accurately foresee what kind of jobs will be created, it is nevertheless, to a certain extent, possible to estimate the kind of skills that will be required for future emerging job roles. Within this context, the respondent specifically mentioned skills associated with data, clouds, and robotization. The relevant findings regarding the potential implications of the job creation effect of automation for future skill requirements will be presented shortly.

As illustrated by the presentation of the findings relating to the different effects of automation on jobs provided above, it is anticipated that, according to the experts interviewed, automation is expected to strongly affect jobs by not only displacing and creating certain job roles, but also by transforming existing job roles. In view of this, while the different effects were frequently addressed by the interview respondents within the context of anticipated skill demand, it was decided by the researcher to not go into too much detail regarding the different effects of automation on jobs as the findings that specifically relate to these effects are considered to being secondary to the findings that are directly addressing potential future skill trends in the context of automation for the purpose of answering the central research question of the present thesis. Nevertheless, it still important to discuss the findings, albeit shortly, as these insights relate to the underlying changes and dynamics that are essential to understand in order to fully grasp why the skill requirements of jobs are expected to undergo substantial changes. Hence, even though these findings do not provide a direct answer to the central research question of this work, it was refrained from excluding them in the present section due to their important implications for future skill trends. Overall, many interview respondents mentioned that they believe that the adoption and implementation of automation technology into the workplace are significantly changing the job or task structure, be it to a lesser or stronger degree, and that these changes entail important implications for future skill trends. In view of this, the study's findings that directly relate to and address the aforementioned anticipated future skill trends, changes, and demand within the context of increasingly automated work environments will be presented in the following.

3.4.2 Skill Categories that are Expected to Increase in Relevance and Demand within the Context of Automation

Advanced cognitive skills

To begin with, several interview respondents reported that they expect a substantial increase in the relevance of advanced cognitive skills in the context of increasingly automated workplaces. For instance, one interviewee noted that, when all the repetitive and routine work tasks will become automated, human workers will need to shift their focus towards the remaining, more challenging work tasks, which, in turn, demand higher-order skills including advanced cognitive skills, such as critical, analytical, and creative thinking along with skills related to complex problem-solving. Moreover, in terms of the relative importance of advanced cognitive skills within a job automation context, another interview respondent provided the example of advisory or consultancy activities. According to the respondent, consultants typically employ quite advanced skills in their everyday work activities, which often center around the task to find an appropriate solution to a particular, specific problem. However, as stated by the respondent, in the case that a specific problem is not only occurring once, but is occurring frequently, thereby developing a repetitive nature, this problem can then become automated due to its repetitive character. With regard to this, the interviewee then noted that, in the future, people will be increasingly required that are able to identify which cases or activities can be automated, and which cannot. According to the respondent, this ability to comprehend and adequately assess which cases can become automated requires specific skills that are advanced in nature.

Further, in terms of the expected relevance of skills related to creativity, one respondent argued that, with ongoing technological advances, workers need to increasingly display higher-level creativity skills. More specifically, the expert interviewed provided the example of an automation technology called GPT-3, which is, according to the expert, a natural language processing and natural language generation model that is based on deep neural networks and that makes use of so-called unsupervised learning in order to produce human-like text including stories, summaries, marketing-type text, as well as job descriptions. According to the expert, GPT-3 also has a so-called creativity setting where "you can use a slightly less probable word […] that gets fed back into the context and then predicts the next word […], so with this totally simple kind of mechanism, it can write stories and that's a very, very interesting advance because all of the preceding techniques for doing text generation with neural networks […] would lose the context after 20, 30, 40 words or something like this […], these new neural networks keep the context for long, long periods of time" (Interviewee 3). Due to this technological advance, the expert stressed that "if you now use this type of program as a writing assistant – and I think we are just two or three more years away before these will be more widespread – we need to now have the people, who before did the creative writing, [to] do work at a higher level" (Interviewee 3). Hence, the respondent argued that, due to ongoing technological advances that may, for example, take over some creative type of work, workers, in general, need to have high-level creativity skills that are superior to those of machines. In relation to the aforementioned points, the same expert also stressed that, when automation technologies, such as GPT-3, may take over some of the simpler writing tasks, it would then assist the worker in not only being more productive, but also would allow the worker to spend much more time on the "really creative work" (Interviewee 3). In line with the points mentioned above, another respondent stressed the importance of the uniquely human creativity skills as these skills are extremely difficult to emulate by automation technologies. As stated by the respondent, "creativity is one thing, which is extremely difficult to emulate, basically, at the human level. There are already a lot of algorithms [that] are trying that and [that] are doing very nice things, […they] can do great work, like generating pictures, and they can generate beautiful artwork […], so I think in some cases the creativity is being very nicely emulated, but, still, I don't think that, for example, when you think about Bach or Beethoven, that any robot will be able to do or write such things because it doesn't have the emotions and the empathy behind it" (Interviewee 5). Consistent with the aforementioned points, another respondent also emphasized the importance of creative thinking skills within increasingly automated work environments. With regard to this, the respondent provided the example of the factory floor and stated, “if more and more simple work tasks and work tasks related to difficult manual and physical work activities will become automated, then inherently human creative-thinking skills as well as skills related to complex cognitive thinking will be increasingly required by humans […]”[5] (Interviewee 2). The respondent further argued that creative-thinking skills are becoming increasingly important “as automation is not able to emulate those skills sufficiently”[6] (Interviewee 2).

In addition, Interviewee 3 also noted that, due to the augmentation potential of sophisticated automation technologies, workers, in general, would have more time to focus on their creativity and problem-solving skills. In terms of the creative thinking skills, the expert stated that, if automation makes one more efficient and productive in one’s job, then one “will have more time for creativity […], to literally have the drudge work that works out the detailed stuff done by software […] and then I can concentrate more on thinking the big thoughts” (Interviewee 3). Further, as stated by another respondent, “creativity is also something useful for problem-solving, as well as [for the] adaptation to difficult situations that are going to arise in seconds” (Interviewee 6). In addition, as stated by Interviewee 3, technological advances in artificial intelligence that would, at some point in the future, enable the invention of general artificial intelligence will be of great support to workers in their respective job roles by, for example, taking over the drudge work, thereby allowing them to spend more of their work time on valuable work tasks, for which they can, to a much higher extent, utilize their problem-solving and creative thinking skills. Further, within this context, the same respondent argued that logical reasoning skills are also very important for workers to obtain or develop as even highly advanced automation technology, such as specific software automation, is still not able to adequately emulate logical reasoning skills. To illustrate his point, the expert referenced the famous quote by Arthur C. Clarke that states that “any sufficiently advanced technology is indistinguishable from magic” (Interviewee 3). In view of this, the respondent remarked that he changed this quote into “any sufficiently advanced pattern matching is indistinguishable from reasoning” (Interviewee 3), thereby emphasizing that “they [the automation technologies] seem to be able to reason, but I am absolutely convinced that they do not reason because they have no semantic understanding of our world” (Interviewee 3). Thus, according to the expert, even

[5] Original German statement: „[…] wenn ich immer mehr einfache Arbeiten, schwere Handgriffe und dergleichen durch Maschinen automatisieren lasse, brauche ich eigentlich immer mehr die Kreativität des Menschen oder das komplexe kognitive Verhalten des Menschen.“

[6] Original German statement: „[…] weil es der Punkt ist, den die Maschine nicht können.“

in the face of highly advanced technologies, work tasks that require logical reasoning skills will still demand human workers as the technological capabilities are still not sufficiently advanced in this domain. In addition, the expert noted that, from a consultant perspective, in this increasingly complex world characterized by ongoing technological advances, consultants need to utilize certain uniquely human skills, especially those relating to the domain of advanced cognitive skills. According to the expert, "from the point of view of a consultant […] clients need a lot of guidance. And those are the important human skills to make sense out of many, many choices and not just in an abstract way, but really having talked to the client, understand their context, what industry are they working in, what problems are they trying to solve, and then guiding them appropriately" (Interviewee 3).

Moreover, in terms of the importance of advanced cognitive skills, one interview respondent, who spoke from a human resource (HR) perspective due to the respondent's professional background in the HR domain, noted that the automation of certain work tasks can allow workers to spend more of their working time on tasks that machines are not sufficiently capable of doing, such as analyzing things. Within this context, the interviewee gave the example of a major HR transformation project that the respondent experienced in the respondent's former job. With regard to this, the respondent mentioned that this HR transformation aimed to make the work of HR managers much more efficient and productive by means of the implementation of a specific platform that would enable the automation of certain HR tasks, such as administrative work tasks. According to the respondent, this technological transformation effectuates that "in the future, when we have one system, we can have a very simple reporting and then we can spend more time on analyzing and things, which the machines maybe cannot do at the moment for us" (Interviewee 7). Further, the same respondent, who, at one point, talked about the need to upskill people due to automation, stated, when asked by the interviewer to relate this upskilling approach to one or more specific skills that the upskilling may aim at, that the upskilling may target, among other skills, critical thinking skills. As stated by the respondent, "in the past, they [the workers] were so focused on doing […] more repetitive tasks and not thinking broader […] and now their jobs [are] really expanding and they have much more time and much more the empowerment to do more greater things than they were doing in the past […], so I would say […] critical thinking" (Interviewee 7).

Further, in terms of the relative importance of higher-order cognitive skills in the context of automation, another respondent provided the example of factories. According to the respondent, there seems to be a growing number of factories in which more and more human workers are getting replaced by modern automation technologies, such as robotics. However, the respondent noted that, while automation clearly reduces the number of people working in a factory, the factories still need workers that are sufficiently proficient to run the factory and that employ a supervisory function in the respective factory for which they need certain higher-order skills, such as skills related to doing diagnoses, processing a large amount of information, thinking critically, and solving problems. As stated by the respondent, those workers that will be running the factory will need very advanced skills "because they need to be able to keep the whole factory running" (Interviewee 3). Thus, according to the respondent, even though there will be much fewer people in the factory, the skill levels of the workers that remain need to be much higher than before. As argued by the respondent, "running a factory is going to be an incredibly highly-skilled job" (Interviewee 3).

In relation to the points mentioned above, another respondent argued that, due to the ongoing digital transformation within the context of automation, workers, in general, need to shift towards a so-called meta-level of cognitive skills in order to be able to keep performing their current job roles. According to the respondent, "this means that I don't need to understand anymore how each work process works, but I rather need to understand how each work process is changing and how I can continuously adapt this process"[7] (Interviewee 8). Within this context, the interviewee provided the example of so-called collaborative robots, also called cobots, that, according to the interviewee, are robots that are capable of working closely next to human workers. As stated by the respondent, "It's quite funny […]. It [the cobot] is capable of doing exactly what the human worker did before. Thus, this means that the worker is not carrying out anymore the repetitive work tasks, but, instead, the worker is showing the cobot once the tasks it need to perform, which are then repeatedly executed by the cobot. This is kind of the vision regarding the future world of work. Hence, instead of doing the work tasks by themselves, the workers are showing the cobots what to do so that they can perform those tasks repeatedly. This, in turn, means that the workers are shifting towards a meta-level, where the worker doesn't perform the tasks by him- or herself, but, instead, demonstrating to the cobot the work tasks that need to be done. […]. Thus, instead of doing things by myself, I shift towards the meta-level [of my cognitive skills] in order to be able to steer someone else in performing

[7] Original German statement: „Das heißt also, ich muss nicht mehr verstehen, wie der einzelne Vorgang läuft, sondern ich muss verstehen, wie sich der Vorgang verändert und wie ich ihn ständig weiter anpasse."

the required work tasks"[8] (Interviewee 8). Within this context, the respondent further argued that "this means that the basic or simple cognitive skills, although they will always be required, will become less relevant. Quite important for the overall success are the advanced [cognitive skills] that enable one to understand how algorithms can be trained, how algorithms can be adapted, how machines are appropriately steered, how the machine needs to set up in order to function correctly so that it can perform those tasks that were hitherto performed by humans […], that's what I mean with the meta-level."[9] (Interviewee 8).

Further, within the context of advanced cognitive skills, the empirical findings also underline the increasing relevance of skills associated with learning, with many respondents having stressed the importance of both the ability and willingness to learn. In view of this, one respondent argued that, as job roles increasingly shift from being based on routine and repetitive work tasks towards job roles that are characterized by project-based work, the work tasks, activities, and projects that workers need to carry out are undergoing constant changes, depending on the respective requirements of, for example, a specific project. Hence, this shift towards more project-oriented work activities where workers are required to do many different things depending on the respective project, necessitate the continuous learning of new skills as each new project may demand different skills, according to the interviewee. As argued by the respondent, this challenge of being able to continuously display the diverse skills necessary to, for example, finishing a project, in turn effectuates the necessity for not only the willingness to learn, but also for developing a lifelong learning mindset. Further, with regard to the importance of skills associated with learning, another respondent agreed when being asked by the interviewer if the respondent would agree to the idea that learning skills will become increasingly important in the near future due to a more and more dynamic world driven by ongoing technological change. More specifically, the respondent stated, while also stressing the

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[8] Original German statement: „Total witzig […]. Er macht genau das, was ein Arbeiter macht. Das heißt also, der Arbeiter macht nicht mehr die sich wiederholenden Tätigkeiten, sondern er zeigt diesem Cobot einmal was er tun muss und der Cobot wiederholt es dann einfach. Das ist so ein bisschen die Zukunftswelt, die man sich da vorstellen kann. Das heißt, anstatt die Tätigkeiten selber zu machen, kommt der Arbeiter in die Situation, dem Cobot einmal zu zeigen, sodass der es dann repetitiv wieder machen kann. Das heißt also, ich komme auf eine Metaebene in der Arbeit hoch, wo ich nicht mehr selber tue, sondern jemand anderem zeige, was zu tun ist. [..]. Und das meine ich damit. Wo ich bisher die Tätigkeiten selber ausführe, gehe ich auf eine Metaebene hoch und steuere wie etwas die Tätigkeit ausführt."

[9] Original German statement: „Das heißt, diese einfachen kognitiven Fähigkeiten werden - natürlich braucht man die weiterhin – aber die werden weniger. Relativ wichtig für den Erfolg sind eben die Fortgeschrittenen zu denken, wie bringe ich dem Algorithmus [etwas] bei? Wie verändere ich den Algorithmus? Wie steuere ich die Maschine? Wie leite ich die Maschine an, um das zu tun, was ich bisher halt selber gemacht hab. Und das ist was ich eben mit der Metaebene meine."

importance of the willingness to learn, that “I think learning is becoming really the epicenter of everything. And it’s really one of the most important factors in this whole transformation because there is no transformation without learning” (Interviewee 7). In addition, another respondent argued that “technology is complex […] and so [is] the new profession of tomorrow […], so I’m seeing that the new profession of tomorrow is likely defined by lifelong learning” (Interviewee 6). Further, when asked if the respondent would agree that learning skills will become increasingly important, the respondent answered that “the ability of learning and to adapt to a new form of learning is definitely something that needs to be defined into the new profession of tomorrow […] because people need to be flexible” (Interviewee 6). In relation to the aforementioned points, another respondent argued that, also against the background of increasing automation of simple, repetitive, and routine-based work tasks, continuous learning is extremely important in order for workers to keep up in this ever more complex and dynamic world of work, that is, among other things, driven by ongoing technological change. According to the respondent, as nobody can afford to stop learning, “learning skills do not only constitute unavoidable skills, but also skills that will become increasingly important”[10] (Interviewee 8). Further, within this context, the respondent also stressed that “one needs to acquire more and more knowledge within an ever-shorter time frame […]. I think that one needs to learn even more in a much faster pace in order to keep up with the exponential [changes shaping the world of work]”[11] (Interviewee 8). Consistent with the points mentioned above, another respondent also stressed the importance of the ability to learn by saying, when asked if, according to the respondent’s opinion, the learning ability is becoming more important, “absolutely. That’s, I think, probably the most important skill […], so it’s very important to being able to learn and [to] want to learn” (Interviewee 5). In addition, the same respondent also emphasized the importance and relevance of the willingness to learn for the ability to learn by stating “and I think that the willingness to learn is even more important than being able to, because if you’re willing, then at some point you will be able to, even if not perfect […], to a certain extent you will be able to if you’re willing” (Interviewee 5).

Social and emotional skills

[10] Original German statement: „[…]. Also insofern nicht nur ein immer wichtigerer Skill, sondern [auch] ein völlig unvermeidbarer Skill.“

[11] Original German statement: „ich muss immer mehr Wissen in immer kürzerer Zeit aufnehmen. […]. Ich muss immer schneller und immer mehr lernen, weil ich dem Exponentiellen […] ja irgendwie mit Schritt halten muss.“

The anticipated increase in the importance and relevance of social and emotional skills within the context of increasingly automated work environments was another theme that was frequently mentioned by the interview respondents.

For example, one manager of a consulting firm noted that, as the automation of simple and mindless work tasks of a given job allows the worker in the respective job role to focus on more valuable and challenging work tasks, the respective worker is then required to display more of the uniquely human skills, such as human intelligence. Consistent with this, another respondent, who talked about the need to upskill people in the face of the increasing usage of automation in the workplace in order for them to be sufficiently skilled, which, in turn, would allow them to keep working in their changing job roles or to do new job roles, noted that, when asked by the interviewer to provide some examples of skills to which this upskilling agenda could relate to, the upskilling may not only be aimed at creative thinking skills as well as technological skills, but also at emotional intelligence skills as well as skills related to working with people. Moreover, with regard to the importance of social and emotional skills within an automation context, one respondent argued that "I think that […] people will definitely maintain the professions that are uniquely human" (Interviewee 6). Within this context, the respondent referenced the example of the job role of a bartender that was introduced beforehand by the interviewer. According to the respondent, bartenders or any workers that work in professions that need to deal with customers need to sense the specific needs of the respective customer, something which is difficult for machines to do. With regard to the bartender job, the interviewee stated that "if I have some allergies to cherries and I want [a] cucumber on my cocktail, then a human is able to directly offer me a cucumber […] because we as humans want to be recognized and we want that our own needs are immediately recognized by the others without even saying that […] we don't want to communicate a lot when we are in need, right? So, according to that, I think that […] people will definitely maintain the professions that are uniquely human" (Interviewee 6).

In addition, in terms of the relative importance of social and emotional skills within a job automation context, another respondent argued that, due to the automation of certain repetitive and mindless work tasks in a given job role, workers are increasingly required to take over the more valuable as well as the more complex work tasks, which, in turn, necessitates the increasing usage of social and emotional skills, such as skills associated with communication and empathy. More specifically, the respondent provided the example of call-center workers that was already mentioned earlier and stated "if automation takes over the simpler customer inquiries, then the tasks of workers shift towards the handling of the more complex customer inquiries. If automation takes over the simple things, then human workers need to handle those cases, where customers are stressed out or irritated and, as a result, explicitly ask for a human worker to get in contact with as the software is not able to manage such complex inquiries […]. Thus, either the machine does not understand the customer's inquiry, or the machine does not have the necessary capabilities to handle the inquiry […]. In the cases, in which the machine does not sufficiently understand the customer's inquiry, or, in which customers are irritated and explicitly ask for human support, then the workers, who will be handling those cases will have to display much more social skills in order to handle the complex or so-called escalation-cases. In situations like that, human empathy is required"[12] (Interviewee 2). The respondent then proceeded by also stressing that, due to the difficulties to advance automation technologies in a way that enable them to adequately emulate social and emotional skills, and due to the so-called uncanny-valley-effect, which, according to the respondent, describes the situation where people are afraid of and disapprove of human-like technologies, the goal is not to innovate automation technologies that can emulate social and emotional skills perfectly. As remarked by the respondent, "[…] that's why empathy will always be a skill that will be increasingly required by humans […]. The more mindless and simple work tasks will be automated, the more empathy is required of humans"[13] (Interviewee 2).

In addition, in terms of skills related to empathy and communication, one respondent argued that those work tasks that are at high risk of being automated refer to those tasks that typically do not require empathy or advanced communication skills as, in terms of communication skills and according to the respondent, human communication is usually complex in nature and, therefore, difficult to be emulated by machines. Accordingly, this means that, in the respondent's view, those work tasks that are routine-based and do not require empathy or

[12] Original German statement: „Wenn ich die einfachen Anfragen von Kunden durch Automaten erledige lasse, bleiben die komplexen Anfragen übrig. Wenn ich die simplen Dinge durch Automaten erledige lasse, bleiben die Themen übrig, wo Menschen gereizt sind und nicht mit einem Software-Automaten reden wollen, wo die Software schlichtweg nicht in der Lage ist, den Menschen zu verstehen, […] was den menschlichen Eingriff erfordert. Und da gibt‘s eigentlich zwei Kategorien von Themen […] die Maschine versteht nicht, was es ist, was der Mensch hier will. Und […] die Maschine kann nicht, was der Mensch von ihr will. […] Wenn ich als Maschine sage hey, ich verstehe den Menschen hier nicht […] oder der Mensch schreit mich die ganze Zeit an […] der will mit einem Menschen reden, er will eskalieren, dann sind die Menschen, die solche Anfragen handlen, viel, viel stärker in der Notwendigkeit von sozialen Skills, weil sie eben die Fall-outs, die Eskalations-Cases, die komplexen Cases handlen müssen. Und dort will ich diese menschliche Empathie haben […].“

[13] Original German statement: „Deswegen wird der Punkt der Empathie nach wie vor etwas sein, was wir immer stärker von den Menschen brauchen […] je mehr stupide, einfache Tätigkeiten wegrationalisiert werden, […] brauchen wir die Empathie des Menschen.“

human-level communication will decline. Hence, as stated by the respondent, "the work tasks that remain to be performed by humans constitute those tasks that require exactly those empathy, communication, and coordination skills that, at least for now, cannot be emulated adequately by automation technologies"[14] (Interviewee 8). Within this context, the respondent further stated that "accordingly, the average skill sets of workers, such as the average communication skills, will increase"[15] (Interviewee 8).

Further, when asked about the relative importance of social and emotional skills within a job automation context, another respondent referred to leadership skills while noting that, especially in the face of digital and technological transformations within the workplace, leaders need to have strong communication skills. In view of this, the respondent noted that one of the first things the respondent learned at the company, for which the respondent worked for a long period of time, that "the order is people, process, technology […]. If you can't convince people to change their ways to adapt [to] business processes that you can then implement with new technologies, nothing is going to happen […] so you need to be able to communicate effectively" (Interviewee 3). Further, in terms of the role of leaders within an increasingly automated work environment, another respondent argued that, besides the expected increase in relevance of advanced coordination and communication skills, the role of leaders will also become increasingly demanding as a result of increasingly complex work environments due to automation. According to the respondent, due to the automation of rather simple, routine-based work tasks, the remaining work tasks that need to be performed by humans will be increasingly complex in nature. As noted by the respondent, this, in turn, changes the leadership styles required to lead and manage effectively. In the expert's view, leadership styles will need to shift in a way that allow for motivation, coordination, as well as the management of self-organizing teams. Similarly, another respondent argued that, within increasingly automated work environments, the leadership role needs to undergo substantial changes. More specifically, the respondent argued that "if you [as the manager] have to manage your employees [that, as a result of automation,] are experiencing increased scope for design [regarding business-related issues and work organization in general], then you, as the manager, need to adapt your skills in

[14] Original German statement: „[…]. Was übrig bleibt, was von Menschen noch gemacht werden muss, sind natürlich dann genau die empathischen, die kommunikativ-intensiven, die koordinierenden Fähigkeiten, die man, zumindest jetzt, noch nicht so schnell ersetzen kann."

[15] Original German statement: „Und dementsprechend ist natürlich der durchschnittliche Skill Set, kommunikative Skill Set, ein ganz anderer als er es heute ist."

a way that enables a shift from a more administrative-oriented leadership style towards an approach that allows for the communication and implementation of the overall goal and mission of your organization […]. This means that, as a result of automation, managers need to become leaders, as, among other things, leading leads to new possibilities, new ways of working"[16] (Interviewee 1).

In relation to the aforementioned points, another respondent stressed the importance of uniquely human skills within ever more automated work environments, while especially referring to the domain of social and emotional skills within a leadership context. In view of this, the respondent provided the example of Donald Trump to emphasize the high importance and relevance of advanced communication skills. As stated by the respondent, "so if you look at Donald Trump […]. I mean, the talking that he's doing or the writing […]. All these things can […] be taken over [by automation]. It can be done by any robot, honestly. But the way he is motivating the crowds, the way he is telling his stories, the way he's basically selling things when he's trying to convince people […], the way he's doing these things […] cannot be done by a robot […], so I don't think, honestly, that a robot will stand there in front of millions […] and get people crazy about itself" (Interviewee 5). In addition, when asked by the interviewer if leaders or managers will increasingly need such social and emotional skills, the respondent stressed that skills related to empathy and emotional intelligence are highly important within this context. As stated by the interviewee, "yeah, empathy, basically […], it's really about this emotional intelligence and empathy. Summarizing things, listing numbers, doing statistics, showing charts […], basically everything that is data-oriented can be easily done [by automation]. But anything […] that involves emotions [and] empathy […], those things are not so easy to automate at all" (Interviewee 5). At a different point during the interview, the respondent, again, highlighted the importance of skills related to empathy by arguing "I think empathy is one thing that cannot be automated because it's unique to each human" (Interviewee 5). Moreover, at another point during the interview, the same respondent also argued that tasks related to making judgements should always be performed by humans. With regard to this, the interviewer provided the example of the work of a radiologist to illustrate the argument. As noted by the respondent, certain work tasks of a radiologist can be automated, such as the task of identifying similarities

[16] Original German statement: „Wenn du Mitarbeiter bekommst, die ein größeres Handlungsfeld, Gestaltungsfeld haben und das auch verstehen, dann musst du als Führungskraft auch deine Skills ändern, nämlich von Verwaltung und Administration zu einer Verständnisentwicklung [in Bezug darauf,] was wir als Gesamtorganisation versuchen zu gestalten, was unsere Mission ist, usw. […]. Das heißt. Führungskräfte müssen sich als Konsequenz der Automatisierung von Managers in Leaders umwandeln, also leading leads to new possibilities, new ways of working."

between the X-ray pictures of several patients that were diagnosed with a certain disease. As stated by the respondent, “this task of identifying similarities is automated already, because any algorithm that is clever enough can do it much better than a human and much faster” (Interviewee 5). The respondent then continued by stressing that, however, the tasks concerning making final judgement should stay within the human domain. As argued by the respondent, “I think judgement should always stay with the humans […]. The final judgement that says if you need an operation or if you have cancer or whatnot, needs to be done by the radiologist, because that’s something that requires […] 15, 20, 30 years of expertise and knowledge, which the algorithm doesn’t have. And then, finally, that will probably also require conversation with the patient and […] adaptability to the situation. So that’s an example regarding what can be automated and what can’t be automated […], so this similarity searching is, for example, in your terms, a declining skill [as it] can be automated. But […] the final judgement cannot be automated” (Interviewee 5).

Technological and digital skills

Moreover, the experts interviewed for the purpose of the qualitative research study conducted in the realm of this thesis frequently mentioned an expected increase in relevance of digital and technological skills within a more automated work and jobs landscape.

For example, one respondent argued that, in the future, more people are required that have the necessary skills that enable them to work together with such technologies. Strengthening this argument, another respondent noted that, as the respondent expects that humans will be increasingly required to collaborate with machines within the coming years, it will be increasingly demanded of workers to obtain or develop the necessary technological and digital skills that enable them to effectively work together with automation technology. Further, another respondent mentioned the growing importance for experts or specialists to have a certain level of digital skills as, according to the respondent, also experts and specialists will be increasingly working together with, and even augmented by automation technologies. In particular, the respondent argued that experts or specialists, such as oncologists, will be increasingly assisted by advanced automation technologies in order to, for example, provide diagnoses or to develop treatment methods. This digital transformation, in turn, according to the respondent, will effectuate substantial changes in the skill requirements of the job roles of such experts or specialists in the sense that more digital skills will be required by them. Within this context, the interviewee also stressed that, with increasing automation and digitalization, basically all workers, be it the more low-skilled workers or the highly skilled workers, such as the specialists mentioned above, will be increasingly required to develop such digital skills in order to be able to effectively work with digital automation systems. As remarked by the respondent, the increasing digital transformations happening within a work environment context are forcing workers of all education- or skill-levels to obtain or develop the necessary digital skills.

However, in relation to the aforementioned points, another respondent stressed, when asked about the future importance of digital and technological skills in the face of the increasing implementation of automation technologies into the workplace, that not all digital and technological skills will be equally important in the future. As stated by the respondent, "it depends on what exact technological skills you are referring to as there are ones that are already very irrelevant" (Interviewee 5). The respondent then provided the example of programming skills, while stressing that an investment in programming skill will be probably worth it in the future. Nevertheless, the respondent then remarked "but then again, it depends on which programming language" (Interviewee 5). In addition, another interview respondent stressed that, in the future, more and more people will be required that not only are capable of collaborating with machines, but also individuals that are able to build and develop such kind of systems. Hence, according to the interviewee, technological competence that enables an individual to, for example, develop a certain software, will increase in relevance with the growing demand for automation technologies. Within this context, the same expert listed so-called STEM skills as those skills that are associated with mathematics and engineering, assist individuals in, for example, building a specific software, while noting that these skills are likely to become increasingly relevant in the future. Interestingly, when asked about the future importance of STEM skills, one respondent noted that, even though the respondent acknowledged that it seems reasonably to argue that, due to the increasing digital transformation in the context of automation, STEM skills will become more important, the respondent also stressed that this expected trend of an overall increase in the relevance of or demand for STEM skills constitutes a generalization to which the respondent would not necessarily agree to. As stated by the expert, "the idea that everybody needs to have strong levels of STEM skills should be viewed as a generalization to which I would not subscribe to"[17]

[17] Original German statement: „Aber dass alle immer mehr von diesen STEM Skills brauchen, glaube ich, ist eine Verallgemeinerung, die ich so nicht unterschreiben würde.“

(Interviewee 8). Further, while acknowledging that it is essential to have people with the necessary and required skills including STEM skills that enable them to understand, adequately evaluate, and control the appropriate functioning of automation technologies, the respondent also emphasized that "it is dangerous to argue that the only thing that counts in the future are STEM skills"[18] (Interviewee 8) as, according to the interviewee, there are certain social and emotional skills, such as communication and leadership skills, that are equally important.

Further, with regard to the importance of technological and digital skills, another interview respondent stressed that the growing usage of ever more sophisticated automation technologies necessitates people that are sufficiently skilled to be able to understand and evaluate these technologies to ensure that they are used in a responsible way. In this context, the expert provided the example of predictive policing, while arguing that some companies used predictive policing techniques that were based on certain technologies that, however, were heavily biased, thereby enabling the irresponsible usage of automation technology. In view of this, the expert stressed that "we need to make sure that, when we use artificial intelligence, machine learning, deep learning technology that depends on being trained by digesting lots of data, that somebody looks at the data and makes sure that it's balanced, so that you don't get such biases in the data […] and that's part of being responsible […]. I think the devil is in the details […]. We need to make sure that we use these tools responsibly" (Interviewee 3). Consistent with the aforementioned points, another respondent also stressed the importance of having people that are able to understand and control how algorithms work as, with the increasing usage of automation technologies, there also comes this social responsibility and responsibility for societies that needs to be acknowledged. According to the respondent, the availability of such skilled workers will become increasingly important. As stated by the respondent, "because, simply the fact that this is a computer that calculates does not mean that the output the computer generates is ethical, correct, fair, or legitimate. This, in turn, underlines the importance of having people that have specific know-how about and deep understanding of such complex algorithms, and which are sufficiently skilled to be able to assess and evaluate them in an adequate manner according to the criteria mentioned above"[19] (Interviewee 8). In the expert's

[18] Original German statement: „[…]. Ich finde es, auf der anderen Seite, aber auch gefährlich zu sagen, [dass das], was in Zukunft zählt, sind nur noch die STEM Skills."

[19] Original German statement: „[..]. Denn die Tatsache, dass das ein Computer ist, der rechnet, heißt ja noch lange nicht, dass das, was da rauskommt, ethisch ist, richtig ist, fair ist, rechtlich ist. Da ist [es] natürlich ganz wichtig, dass wir Leute haben mit sehr, sehr viel Know-how und sehr viel Verständnis, die diese komplexen Algorithmen auch nach solchen Kriterien beurteilen und bewerten können […]."

view, there will increasingly be workers that will specialize on controlling and evaluating automation technologies, such as machine-learning algorithms, according to the specific criteria mentioned above, and that will be sufficiently skilled to be able to develop sophisticated mechanisms that allow for the control and evaluation of increasingly advanced and complex automation technologies including machine-learning algorithms. According to the respondent, those job roles require, to a certain degree, highly advanced skills including mathematics skills and algorithmic skills that, however, still need to be further developed in the future in order to meet the required skill demands of those job roles. As stressed by the respondent, "if algorithms will be increasingly taking over decisions in our society and if they are becoming more and more complex and advanced in their self-learning and self-developing capabilities, then it will be all the more important to have so-called algorithm-police officers that can identify, control, and prevent possible aberrations of these algorithms. And this requires very deep know-how that, I believe, does net yet exist today"[20] (Interviewee 8).

Systems skills

Further, several interview respondents mentioned that systems skills will increase in relevance within the coming years due to the expected increase in the adoption and implementation of modern automation technologies into the workplace.

For instance, in terms of the importance of systems skills, one respondent argued that, in order for human workers to collaborate effectively with automation technologies in a given work environment, those workers need to be proficient in systems skills. More specifically, the respondent, again, referenced the example of software automation in call-centers that the respondent introduced in the beginning of the interview, and which was also already mentioned earlier in this section. As explained by the respondent, "if I am the person that needs to take over the so-called escalation-cases from the artificial intelligence system, then I have to understand how to work effectively with it. I need to have this understanding, and this relates to a specific skill that develops with the interaction with these machines. I need to understand why I need to take over those more complex cases that the software can't handle. […] I need to understand why the automation software failed in this case. [I need to understand] why I

[20] Original German statement: „Wenn Algorithmen viel mehr Entscheidungen in unserer Gesellschaft übernehmen und immer komplizierter selbstlernend, selbstentwickelnd werden, [wird es] natürlich umso wichtiger, dass wir, ich sage mal, Algorithmen-Polizisten haben, die Fehlentwicklungen in solchen Algorithmen kontrollieren und vermeiden können. Und da ist sehr, sehr tiefen Know-how erforderlich, das wir, glaube ich, noch nicht haben."

have to take over from this point […]. And when I come to the point where I understand the whole system, I need to have the understanding of why the system failed, what the mistake of the software was, what the problem was […]. And this is, to a certain extent, a technical understanding as they are machines, but not technical on a programming level, but technical with regard to how the system works. This relates to a certain approach to understand the reasons for why I need to take over those escalation-cases. This relates to a specific skill, a specific approach for how I do my job"[21] (Interviewee 2). The respondent then proceeded by relating the importance of systems skills to the augmentation effect of automation by stating that "many call agents welcomed the introduction of automation technologies into their work environment as automation is able to take over the mindless work tasks so that one can concentrate more on, for example, the customer dialogue. This, in turn, means that one needs to have an understanding of how the system works as well as an understanding of how I can optimize the system and to understand that this optimization of the system is also beneficial for me as the worker. And, therefore, I need to understand the system. That's why customer-service workers need to have an understanding of what the artificial intelligence is doing and why it is doing what it does. And in what ways does this system help me?"[22] (Interviewee 2). All in all, as stated by the interviewee, skills related to systems skills, such as being able to understand how the machines work, what the machines are capable of doing, what the limits of those technologies are, and to relate those aspects to a specific context, will be growing in importance with increasing technological advances and progress as such technological change intensifies the necessity for workers to interact with such systems. Consistent with this, another respondent argued that, within the context of automation, systems skills are extremely important. More

[21] Original German statement: „Wenn ich der Mensch bin, der die Eskalationsfälle von KI bekommt, dann muss ich verstehen, wie ich damit arbeite. Ich muss verstehen, und das ist ein Skill, der entsteht in der Interaktion mit diesen Maschinen. Ich muss verstehen, warum kriege ich Eskalationsfälle? […] Der Mensch muss verstehen, wie er damit umgeht. […] Ich muss verstehen, warum die [Maschine] ausgefallen ist. Warum übernehme ich jetzt hier? […] Und wenn ich an einen Punkt komme, das Gesamtsystem zu sehen, muss ich an einem Punkt sein, okay, wenn ich jetzt sehe was der Fehler war, was das Problem war […]. Das ist ein technisches Verständnis zum gewissen Punkt, weil es sind halt Automaten […]. Jetzt nicht technisch auf Programmierebene, sondern technisch auf Warum funktioniert das so? das ist eine gewisse Herangehensweise, die notwendig ist, zu sagen Hey ich übernehme Eskalationsfälle. Das ist ein gewisser Skill, ein gewisser Habitus, mit dem ich an den Job rangehen muss."

[22] Original German statement: „[…] In anderen Projekten wurde die Einführung dieser Technologies sehr, sehr begrüßt, weil die Agenten wissen, hey, ich kann jetzt mit einem System zusammenarbeiten, sodass ich viel, viel weniger stupide Arbeit machen muss und ich mich mehr auf den Kundendialog konzentrieren kann oder so. Und das heißt, dazu brauche ich ein Verständnis was dieses System tun wird und Verständnis, wie ich das System besser machen kann und dass es mir was bringt, dieses System besser zu machen. Und dazu muss ich das System verstehen. Dazu muss ich als Kundenservice-Mitarbeiter ein Verständnis dafür haben Was macht diese KI jetzt hier? Warum macht sie das? Und was bringt es mir?"

specifically, to illustrate this argument, the respondent provided the example of digital twins and argued that, within the era of the fourth industrial revolution, digital twins, which are specific automation constructs that, among other things, understand exactly how, for example, a factory looks like and what the spatial and physical limits are, will become more commonplace. In view of this, according to the respondent, workers need to be capable of understanding, among other things, the context in which they work, which kind of machines are implemented in the work environment, what kind of capabilities the machines entail, and how such digital twins can be steered and optimized. In the view of the respondent, "[…] this then requires a systemic thinking that has a whole other dimension compared to today […]. This is a substantially different world, in which systems skills are extremely important."[23] (Interviewee 8). Nevertheless, while another interview respondent stated that systems skills are likely to increase in relevance, the same respondent also stressed that, based on his life experience, there are not many people who, at present, have those systems skills as those skills not only require a thorough understanding of the technologies at hand, but also an adequate understanding of the socio-economic environment along with a certain level of social and emotional skills. According to the respondent, while it is exactly this interplay of skills that enable people to display systemic skills, there are not many people that have the specific combination of skills that make up systems skills.

3.4.3 Skill Categories that are Expected to Decline in Relevance and Demand within the Context of Automation

Physical and manual skills

To continue, none of the respondents directly addressed the future importance or expected trend of physical and manual skills. Nevertheless, two interviewees still voiced their opinion regarding physical and manual skills within the context of automation. For example, one respondent, while not specifically addressing the anticipated future trend concerning physical and manual skills within a job automation context, stated that it would be very efficient and productive for automation to take over the physical and manual tasks, thereby enabling workers to spend more of their time doing more valuable work tasks. As stated by the respondent, "I mean, what happens with knowledge work is what happens with factory work, with agricultural

[23] Original German statement: „[…]. Das ist dann natürlich ein Systemverständnis, welches ich haben muss, [und] das eine ganz andere Dimension hat als es heute der Fall ist. […]. Das ist eine ganz andere Welt und da sind diese System Skills natürlich extrem wichtig."

work, etc. […], so doing these repetitive physical things are very difficult for us humans […], doing these repetitive knowledge-work things […], it's also exhausting […], it's boring, and you come home [and] you kind of go like what did I do all day? [...]. I didn't really do anything […]. I didn't do anything creative in that sense […]. And I think if all the drudge work [would be] taken away in the physical realm by having robots, […then] people will do great things […], and the same is true for knowledge work" (Interviewee 3).

Interestingly, another respondent argued that certain manual skills, such as skills related to finesse, are difficult for machines to adequately emulate. As stated by the respondent, "you probably know that machines can do a lot of things repetitively, but what defines the human capacity is the finesse […], so the ability to do certain things with our fingers, our sense of touch […], and this is really difficult to be emulated by machines" (Interviewee 6). However, the same respondent also stressed her hopes that in the future, there will be machines that have the necessary capabilities to take over the specific tasks in the physical and manual domain that hitherto are done by humans. According to the respondent, "we are in a new era of automation […], we will have new sort of machines that will be able to collaborate more closely with humans, with the employees […], so we will have a new generation that I really hope to see […] in the proximal future […], a new kind of complex and really useful […] automation solution that will have to cover these specific tasks that now are mainly done by humans" (Interviewee 6).

Basic cognitive skills

In terms of basic cognitive skills, several experts noted that modern automation technologies are becoming increasingly sophisticated and advanced in their capabilities that enable them to perform tasks that, to a large extent, demand basic cognitive skills. For example, one respondent discussed the example of a language-generation tool called GPT-3 that, according to the expert, is based on deep neural networks and unsupervised learning, and that can generate different kinds of texts including stories, summaries, marketing literature, as well as job descriptions, thereby being able to take over such tasks requiring only basic cognitive skills, such as basic writing skills. In addition, within this context of the future importance of basic cognitive skills, one respondent provided the example of reading and argued that reading skills can be easily emulated by modern automation technologies, while, however, also stressing that "decline" may not be the correct word to refer to the future trend concerning basic cognitive skills as, according to the respondent, reading skills will always remain a very important skill to have.

As stated by the respondent, "maybe declining is not the word I would use. I mean, we will always read, right? So, provided we are not disabled or anything that keeps us from reading, that will not be going to go away, but those things will become more automated" (Interviewee 5). Furthermore, when asked by the interviewer about the implications for affected workers in this context, the respondent then emphasized that affected workers, whose jobs are threatened by automation, need to upskill or reskill. In addition, when asked by the interviewer whether the respondent sees a shift in demand in the future from basic cognitive skills towards advanced cognitive skills, the respondent agreed. As stated by the respondent, "yes, absolutely […]. We need to acquire those [advanced cognitive skills…]. If you have to work, if you want to stay relevant, then upskilling and reskilling is a must" (Interviewee 5).

3.4.4 The Combination of Diverse Skills

In addition, when asked about the relevance for workers to have a diverse portfolio of distinct skills within the context of an increasingly automated world of work, several interview respondents stated that they believe that, in general, holding high levels of a variety of distinct skills will be especially helpful for workers to thrive in the future world of work increasingly driven by automation. More specifically, the skill categories that the respondents mentioned within this context include technological and digital skills, social and emotional skills, advanced cognitive skills, as well as systems skills. For example, when asked about the future importance for workers to hold a diverse portfolio of skills within the context of increasingly automated work environments driven by the growing implementation of new automation technologies, one respondent argued that, on the one hand, workers with strong digital and technological skills need to also be sufficiently skilled in strong communication skills, while, on the other hand, workers that, hitherto, did not focus so much on the development of their digital and technological skills and that, instead, have strong skill levels in another skill domain, such as social and emotional skills, need to obtain or develop stronger levels of the digital and technological skills in order to work effectively in anticipated future technology-driven workplaces. As argued by the respondent, workers need to be able to "bridge the gap" (Interviewee 3) between "the intersection of business and technology" (Interviewee 3). According to the respondent, "It cuts both ways […]. The people that used to not care about the technology, they now have to care about the technology and the technologists, who didn't use to care about the business, have to care about the business […], so the technology people or technology-oriented people need to be able to talk business […], make themselves understood,

[…so] I think it cuts both ways […], that those are going to be the successful people that can bridge that gap" (Interviewee 3). In addition, when asked about the relevance or importance for workers to be able to display strong levels of a variety of distinct skills in order to stay attractive in the future labor market within the context of increasingly automated work environments, another respondent mentioned that the combination of digital and technological skills as well as social and emotional skills would make a worker especially attractive. However, as a side note, the respondent also stressed that the so-called "people skills", such as communication skills and adaptability skills, are even more important to focus on as they are much harder to develop and learn compared to digital and technological skills, while still stressing the important combination of both social and emotional skills as well as digital and technological skills.

Further, with regard to the importance for workers to hold a diverse skill set, another respondent argued that, as the new professions of tomorrow will become increasingly complex, having a portfolio of hybrid skills will become increasingly important in this new era of automation, while specifically referencing the importance of digital and technological skills, advanced cognitive skills, as well as social and emotional skills. With regard to the importance of digital and technological skills, the respondent stated that "engineers need to have hybrid skills […]. They need to put themselves in the position of the technician that will use the machines" (Interviewee 6). Within this context, the respondent provided the example of skills that are related to dealing with big data and working with complex algorithms. Further, throughout the interview, the respondent specifically referred to the importance of STEM skills, learning and adaptability skills, skills related to dealing with both people, such as empathy, and related to the digital, technological solutions, skills associated with analyzing data and organizing things, analogical understanding, as well as creative thinking skills, as, according to the respondent, "creativity is something valued […], we also want that our engineers and our technicians will be creative" (Interviewee 6).

Moreover, when asked if there is a particular combination of different skills that will be especially attractive for workers to have in the near future within the context of automation, another respondent noted that a combination of social skills, creative thinking skills, together with systems skills would constitute an optimal combination. The interviewee related his response to the situation, in which humans and machines are closely working together, while saying that "more social skills are required by humans compared to the situation, in which automation is not adopted and implemented within the working environment context, because the cases the workers have to work on demand high-level social skills. In the case of software automation or within the context of factory floors, more creativity is required compared to the situation, in which workers have to handle the mindless work tasks, as the mindless work tasks are becoming increasingly automated by robotics. On the other hand, one will need the systems skills in order to work with machines effectively […]. Hence, it would be a combination of social and creative skills, combined with a certain degree of digital openness, as well as certain systems skills […]. I think that would be an optimal combination”[24] (Interviewee 2).

After having presented the relevant findings obtained by means of the expert interviews that were considered relevant by the researcher to contribute to answering the central research question of the present thesis, the subsequent chapter builds on the insights presented throughout the present section by discussing the interview study’s findings and insights in relation to the most relevant findings derived from the literature review with regard to anticipated future skill trends and demand within the context of automation in order to identify possible consistencies and contradictions between the two data sources, thereby aiming to arrive at a final conclusion with regard to expected skill trends, changes, and demand within the context of increasingly automated work environments. In addition, a discussion outlining a number of important implications of the overall findings will conclude the following chapter.

[24] Original German statement: „[…] Weil ich brauche von diesen Menschen mehr soziale Skills, als das in einer komplett nicht digitalisierten Welt notwendig ist, weil die Fälle, mit denen sie arbeiten, höhere soziale Skills benötigen. Wenn ich jetzt bei Software-Automaten bin oder im Factory Floor brauche ich mehr diese Kreativität, als das vorher beim stupiden Arbeiten [der Fall] war, weil die stupiden Teile ja mehr und mehr durch Roboter gemacht werden. Auf der anderen Seite brauche ich diese Systems Skills, um mit einer Maschine arbeiten zu können, um Hand in Hand gemeinsam arbeiten zu können […]. Deswegen [ist] eine Kombination dieser Themen, dieser sozialen, kreativen Skills verbunden mit einer, ich sage mal, digitalen Offenheit und gewissen systemischen Skills, denke ich, eine optimale Kombination.“

4 Discussion and Practical Implications

4.1 Discussion: Synthesizing Findings from Relevant Literature and the Qualitative Research Study

The present thesis aimed to provide a coherent answer to the central research question of this work that asked how job automation is changing the skill requirements of jobs within the context of advanced economies. In order to generate a valuable response to this question, an extensive literature review as well as a qualitative research study in the form of expert interviews were conducted. Hence, both secondary data in the form of key literature findings as well as primary data in the form of interview data were collected within the realm of this work in order to reach the objective of answering the central research question of this thesis in a coherent, data-rich, and valuable manner. Based on this, the following discussion will summarize the key findings from the interview study that were presented in the preceding chapter and will then relate those main findings to the key literature findings that were already outlined in Chapter 2.4.

Before proceeding with the discussion, it is important to stress at this point that, for the purpose of answering the central research question of the present thesis, the following discussion will focus exclusively on the findings addressing the anticipated future skill trends in the context of job automation, thereby refraining from thoroughly discussing the different effects of automation on jobs that were already addressed extensively in both Chapter 2.4.1 as well as in Chapter 3.4.1 of this work. As shown in both Chapter 2.4.1 as well as in the foregoing chapter when presenting the key findings of the expert interviews, the increasing adoption and implementation of modern automation technologies into the work environment are expected to substantially affect the occupational structure as well as the nature of jobs within the context of advanced economies, and that these dynamics and changes will, in general, have direct and important implications for the skill requirements of jobs (see e. g. Manyika et al., 2017; Manyika, Lund, Chui et al., 2017; Nedelkoska & Quintini, 2018; Servoz, 2019; Vazquez et al., 2019; WEF, 2018). Hence, due to their important implications for potential future skill trends, changes, and demand in increasingly automated work environments, the researcher deemed it necessary to not only discuss the varying effects of automation on jobs in Chapter 2.4.1, but to also address these effects, albeit shortly, in the beginning of Chapter 3.4, which presented the findings from the interview study, in order to contribute to an overall and deeper understanding of the dynamics underlying the potential future skill trends, changes, and demand within the context of automation. According to the researcher, obtaining this understanding is crucial to fully comprehend the "how" of the question asked in this research project. Nevertheless, due to the limited scope of the present thesis as well as for the purpose of focusing on answering the central research question of this thesis, the following discussion will solely outline the key themes that are directly concerned with the anticipated future skill trends, changes, and demand. Thus, in the following, the differing effects of job automation will not be discussed as key themes, but will rather be, when deemed necessary for the purpose of illustrating or underlining a specific point, integrated into the key themes that directly reference the expected future skill trends along with the associated skill categories.

Overall, it seems reasonably to argue that both the findings from the qualitative research study and literature review conducted in the realm of this thesis point toward expected changes in the skill requirements of jobs as a result of increasingly automated work environments. Nevertheless, while most of the findings of the interview study are in line with the literature findings presented in Chapter 2.4, a number of noteworthy irregularities or inconsistencies that could be identified in the interview data will need to be acknowledged. In view of this, the remainder of this section will discuss, in detail, the key findings relating to the central research question and will provide a discussion about their meaning and interpretation.

4.1.1 Skill Categories that are Expected to Increase in Relevance and Demand within a Job Automation Context

To start with, consistent with the findings derived from the literature, the findings that resulted by means of the analysis of the interview data also suggest that certain skill categories as defined in Chapter 2.4.2 are likely to increase in relevance or demand within the context of job or task automation. In light of this, the key insights relating to each of those categories along with their meaning and interpretation will be discussed in the following.

Advanced cognitive skills

To begin with, the findings yielded from the qualitative research study clearly suggest that advanced cognitive skills are becoming more important and relevant for workers to obtain and develop within a job automation context, as, according to several interviewees, those skills are difficult to be emulated adequately by even sophisticated automation technologies. In particular, within this context, the interview participants frequently mentioned, among other skills, the increasing importance and relevance of critical and creative thinking skills, complex problem-solving skills, as well as learning skills. Hence, the findings from the interview study are largely consistent with the literature findings presented earlier in this thesis. As thoroughly outlined in Chapter 2.4.2, the relevant literature commonly indicates that advanced cognitive skills, especially skills relating to the ability to learn, are expected to increase in relevance within the next few years as a result of increasingly automated work environments (Bakhshi et al., 2017; Bughin et al., 2018; Cedefop, 2018; Manyika, Lund, Chui et al., 2017; Rainie & Anderson, 2017; Tytler et al., 2019).

As already indicated above, skills related to learning emerged, consistent with the findings derived from the literature, as a frequently mentioned theme during the expert interviews. Hence, the overall findings suggest that, although many other advanced cognitive skills seem to increase in demand in the near future in the context of automation, skills related to learning seem to be one of the most important skills to obtain or develop in order for workers to thrive in the anticipated future world of work. This insight, in turn, has important implications for various stakeholders, which will be further discussed in the subsequent section.

Further, another aspect that needs to be addressed in more detail within this context of advanced cognitive skills and their anticipated future trend relates to the implications of ongoing technological progress and its potential implications. As the findings from the interview study suggest, technical automation potential is increasing continuously, which means that some technologies can demonstrate quite remarkable cognitive skills, especially with regard to creativity. In relation to the aforementioned points, one finding derived from the literature seems worthwhile to discuss within this context. As argued by Bughin et al. (2018), due to the ongoing technological progress in terms of modern automation technologies that results in ever-advancing capabilities of already sophisticated automation technologies, certain cognitive skills can already be adequately emulated by such technological applications. More specifically, the authors provided the example of modern technology that entails the required capabilities to write, for instance, simple news stories, and argued that this technological progress is likely to effectuate a certain stability or even a decrease in the demand for specific cognitive skills, such as writing skills (Bughin et al., 2018). This point, in turn, suggests that, as certain work tasks are, to a large extent, based on or require those cognitive skills that modern automation technology can emulate adequately due to their sophisticated capabilities, human workers will be increasingly required to shift towards work tasks demanding, to a large extent, skills that modern automation technology cannot easily emulate properly, such as advanced cognitive skills associated with sophisticated creative thinking skills. This suggestion is in line with the argument provided by Bughin et al. (2018), who argued that the demand for cognitive skills is expected to shift from basic towards higher cognitive skills. In view of this, the insights presented above, in turn, imply that the more advanced and sophisticated automation technologies will become, the more advanced will become the skills that will be required from human workers in order to sustain their competitive advantage in terms of certain skills or skill categories, be it advanced cognitive skills or skills related to other categories. This insight, in turn, has important implications for the average skills required from workers in general as emphasized by one expert from the interview study, albeit in a different context when discussing the future relevance of social and emotional skills. As argued by the respondent, as the more simple and lower-order skills will become increasingly automated, the average skill set required from workers to remain relevant will increase. Thus, this means that, when looking at this insight in a more generalized vein, that the average skills demanded from workers will increase with ongoing technological progress as the modern automation technologies will become ever more sophisticated. This possibility of a consistent increase in the average skills required has important implications, for example for educational institutions, that will be further discussed shortly.

Another point worth to discuss in more detail within this context of the expected future relevance of advanced cognitive skills pertains to one interesting insight provided by one expert interviewed, who argued that “creativity is also something useful for problem-solving, as well as [for the] adaptation to difficult situations that are going to arise in seconds” (Interviewee 6). This statement suggests that, one the one hand, certain advanced cognitive skills that are expected to increase in relevance as a result of increasingly automated work environments, such as creative thinking skills, may have a complementary effect on other advanced cognitive skills, such as problem-solving skills. On the other hand, this insight also implies that the proficiency in a certain skill that pertains to a certain skill category, such as having high levels of creative thinking skills, may be complementary to skills pertaining to a different skill category, such as adaptability or flexibility that, according to the skills classification developed for the purpose of this thesis, relates to the category of social emotional skills. This aspect of possible complementarities between skills pertaining to different skill categories according to the classification provided in Table 1 is also implied by one response provided by an interviewee (Interviewee 5), who noted that even very sophisticated automation technologies do not, at least for now, hold the necessary capabilities to adequately emulate advanced cognitive skills, such as complex creativity skills, also due to the fact that these technologies do not entail the necessary skills related to emotions or empathy that are, as suggested by the expert interviewed, important to display high levels of creative thinking skills. Hence, consistent with the aforementioned points, this argument provided by the interviewee seems to further strengthen the above-mentioned point of potential complementarities between distinct skills or skill sets. Hence, this potential complementarity between not only skills from the same skill category, but also between skills pertaining to different skill categories, constitutes an interesting finding that may be worth to explore further through future research. In the realm of this thesis, this insight is classified as an interesting finding because none of the literature sources reviewed for the purpose of the extensive literature review conducted in the realm of this thesis seem to have addressed this point. This, in turn, implies that it may be worthwhile to conduct more research that addresses this insight in order to further explore the potential complementarities between different skills from not only the same category but also skills pertaining to different skill categories according to the skill classification developed for the purpose of this thesis, as well as how the potential complementarities between skills may assist workers in dealing with the increasingly dynamic and complex world of work characterized by ongoing technological changes in terms of automation.

All in all, as already indicated above, the findings obtained by means of the expert interviews conducted in the realm of the qualitative research study carried out as part of this thesis indicate that, based on the responses provided by the interview respondents, that the skill category of advanced cognitive skills will increase in importance and relevance within the next few years as the skills pertaining to this skill category prove difficult, or even impossible, to be adequately emulated by even sophisticated automation technologies. This point is also underlined by one of the responses provided by one interviewee, who referenced the famous quote by Arthur C. Clarke, who stated that “any sufficiently advanced technology is indistinguishable from magic” (see e. g. Munkittrick, 2011), when arguing that, in fact, “any sufficiently advanced pattern matching is indistinguishable from reasoning” (Interviewee 3). Hence, just as individuals may perceive very sophisticated technology as some magical endeavor due do its remarkable and astonishing nature of its capabilities (see e. g. Karsten & West, 2016), individuals may also perceive extremely advanced pattern matching, which, for example, certain machine learning applications are capable of demonstrating (see e. g. Schmelzer, 2019), as being equal to the skill of reasoning. However, just as very advanced technology does not equal magic (see e. g. Karsten & West, 2016), any sufficiently advanced pattern matching is not equivalent to the skill of reasoning. Thus, even though it may seem that these technologies entail the capabilities to reason, they, in fact, do not as, in the words of the expert interviewed, “they have no semantic understanding of our world” (Interviewee 3). As already indicated, this example seems to be a good illustration that, even though certain advanced technologies are perceived in doing magical things like reasoning, they, in fact, still entail many limitations that, in reality, restrict their capabilities, thereby allowing human workers to remain superior and keep their competitive advantage in certain areas of the working life.

Further, even though it was not explicitly stated by the respondents that the skills associated with this skill category of advanced cognitive skills will experience a definite increase in their demand within the next few years, the responses given as well as the wording used by the experts nevertheless imply that, besides an increase in importance and relevance, it seems highly likely that these skills will experience an increase in their demand due to the reason provided above relating to the technical capabilities of modern automation technologies. Hence, one can argue that the findings derived from the interview study are consistent with the findings derived from the literature, which clearly suggest, as already thoroughly illustrated in Chapter 2.4.2, that advanced cognitive skills are expected to increase in demand, thereby shaping the skill requirements of jobs accordingly.

Social and emotional skills

To continue, in terms of the relative importance and relevance of social and emotional skills within a job automation context, the findings from the interview study demonstrate a clear pattern. More specifically, the findings suggest that skills associated with the domain of uniquely human social and emotional skills will, in general, increase in relevance as, in accordance with the argument provided when discussing the future trend of advanced cognitive skills, those type of skills prove difficult for automation technologies to emulate adequately. In view of this, the findings obtained by means of the qualitative research study seem to be, again, in line with the literature findings presented earlier, which also suggest that inherently human social and emotional skills constitute important skills for workers to possess in order for them to succeed in increasingly automated work environments (Bughin et al., 2018; Cedefop, 2018; Manyika, Lund, Chui et al., 2017). Based on this, the literature findings generally point towards a likely increase in the relevance of as well as demand for social and emotional skills within an automation context (see e. g. AIG, 2018; Bakhshi et al., 2017; Bughin et al., 2018; Oschinski & Wyonch, 2017; Servoz, 2019).

Nevertheless, even though the findings from the interview study seem to, overall, be consistent with the findings from the literature review that suggest a likely increase in the demand for social and emotional skills as a result of increasingly automated work environments, it needs to be emphasized at this point that the responses provided by the experts in the realm of the interview study generally refer to an expected increase in the importance and relevance of these skills, while not specifically claiming an expected increase in the overall demand for skills pertaining to the skill category of social and emotional skills. However, based on the responses given by the experts, one could argue that the interview findings generally point towards not only an expected increase in the relevance and importance of social and emotional skills in the context of automation, but also to a likely increase in the demand for these skills as can be deferred from the arguments provided by the respondents, who argued that, as already mentioned above, uniquely human social and emotional skills are extremely difficult for automation technologies to emulate properly.

Moreover, one additional aspect that seems worthwhile to be further recognized and discussed within this context as this aspect could not be identified in the literature reviewed for the sake of the literature review conducted in the realm of this thesis relates to the so-called Uncanny-Valley-effect that was mentioned by one of the experts when discussing the expected future trend of social and emotional skills. As described by Caballar (2019), the Uncanny-Valley refers to the "observation that as robots appear more humanlike, they become more appealing – but only up to a certain point. Upon reaching the Uncanny Valley, our affinity descends into a feeling of strangeness, a sense of unease, and a tendency to be scared or freaked out. In view of this, the Uncanny Valley can be defined as people's negative reaction to certain lifelike robots" (Caballar, 2019, p. 1). This definition is in line with the description provided by the interview respondent, who further argued in this context that, due to the Uncanny Valley situation, the ultimate goal is not to innovate automation technologies that can emulate uniquely human social and emotional skills perfectly. Hence, this insight, in turn, implies that, even though the possibility may exist that automation technologies may potentially be advanced in a way that enable them to adequately emulate social and emotional skills, this is, based on the interview findings, not the ultimate goal of innovators due to the Uncanny-Valley effect described above. This seems to be a valuable insight as it further underlines the argument that human workers will increasingly need to utilize their social and emotional skills as a result of automation, which, in turn, further strengthens the findings pointing towards an expected increase in relevance of and demand for skills associated with the category of social and emotional skills. In view of this, the concept of the Uncanny-Valley effect was deemed interesting to mention in this context as this insight seems to further support the findings from both the literature and the interview study that suggest an increase in the demand for those skills.

Before concluding the discussion addressing the excepted future trend of social and emotional skills, there is one important last aspect relating to the interview study's findings that, however, was not mentioned by the various literature sources reviewed in the realm of the literature review presented earlier, and, thus, seems worthwhile to further discuss in more detail at this point. As mentioned by several interview respondents when discussing the future trend of social and emotional skills, the role of management and leadership in the context of increasingly automated workplaces is likely to experience substantial changes within the coming years. For example, one respondent argued that, due to the increasing complexity of the working world as a result of changes brought about by automation, the leadership role needs to undergo substantial shifts, while another respondent remarked that "[…] as a result of automation, managers need to become leaders […]" (Interviewee 1). This insight that points toward the necessity of changing roles of managers and leaders as a result of automation also implies that there will likely be changes in the skills required from workers holding a management or leadership position as already indicated by several experts interviewed in the realm of the qualitative research study. In view of the aforementioned points, it may be emphasized at this point that the insights derived from the expert interviews do not only suggest a likely increase in demand for common leadership skills, such as skills related to communication, persuasion, and coordination, which, according to the skill classification developed for the purpose of the present work and as presented in Table 1 pertain to the category of social and emotional skills, but also point towards a change in the leadership skills that will be increasingly demanded within the next few years due to the challenges posed by increasingly automated work environments. In other words, the findings derived from the expert interviews do not only imply an increase in the demand for leadership skills, but also an expected change or shift in skills increasingly demanded in leadership roles within the context of increasingly automated work environments. In relation to these insights and in terms of the findings obtained by means of the literature review, the literature findings merely emphasize, albeit sparsely, a likely increase in demand for skills associated with leadership (see e. g. Bughin et al., 2018; Rainie & Anderson, 2017; WEF, 2018), and thus, do not acknowledge the additionally expected changes or shifts in leadership skills that are suggested by the findings derived from the qualitative research study.

In view of this, it may be inferred from the aspects discussed above that, even though the literature reviewed within the realm of this work generally suggest a likely increase in the demand for skills associated with leadership as already stressed above, the findings from the interview study generally reflect a much deeper urgency or imperativeness when addressing the anticipated changes in the skill requirements of management or leadership roles compared to the literature findings due to the insight derived from the expert interviews that suggests that, in addition to the anticipated increase in the demand for skills pertaining to the category of leadership skills, it is also expected that there will be changes in terms of the required skills within the category of leadership skills. This communicated urgency or imperativeness is also generally reflected in various additional literature sources that commonly argue for the necessity to give more attention to the potentially significant changes in the skills demanded from leaders within increasingly automated work environments (see e. g. Allan, 2020; Harter, 2020; Vinters, 2018). Hence, even though some literature sources reviewed for the purpose of the literature review conducted earlier point towards an upward change in the demand for leadership skills, the findings from the interview study seem to enrich those findings obtained from the literature by implying that more attention should be given to the expected changes in the skill requirements of management or leadership roles. Hence, this insight, in turn, may inspire future research that may contribute to a more in-depth understanding of the anticipated changes in the skill requirements of jobs that specifically pertain to management and leadership roles. Moreover, in light of the above-mentioned insight derived from the expert interviews that suggests that there likely will be changes within the skill requirements of leadership or management roles, future research may also explore if the availability or supply of current leadership skills within the overall skills market meets the expected future demand for leadership skills, thereby identifying potential skill gaps that, as will be discussed in more detail in the subsequent section, also entail important implications for various societal stakeholders.

All in all, in view of the points discussed above, it may be concluded from both the literature as well as the interview findings that social and emotional skills are expected to increase in relevance as well as in demand as a result of increasingly automated work environments, thereby shaping the skill requirements of jobs accordingly.

Technological and digital skills

Moreover, all in all, the findings from the interview study further indicate an expected increase in the relevance of technological and digital skills within a more automated work environment. As frequently pointed out by the respondents, workers will need to increasingly obtain or develop technological and digital skills in order to be able to work efficiently and effectively with automation technologies. This insight also clearly underlines the augmentation effect of automation that was also discussed in the preceding chapter presenting the study's findings. Hence, the findings indicate that workers will need to increasingly obtain or develop the technological and digital skills that are required in order to work effectively together with automation technologies, and thus, to fully seize the augmentation potential offered by automation. The potential and opportunities for businesses that establish an effective collaboration between human workers and automation technologies was also addressed by Newman (2020). In particular, Newman (2020) argued that companies that effectively establish a so-called combined human-machine workforce have considerably better chances in implementing successful digital transformations within their companies, and to ultimately increase business revenue. In view of this, Newman (2020) stated that "I consider the companies that harness the power of humans and machines will be the ultimate winners of the future of work" (Newman, 2020, p. 1). This point is also underlined by Wilson and Daugherty (2018), who, on the one hand argued that companies that are implementing automation solutions for the main purpose of displacing their workers, thereby placing too much emphasis on the displacement effect of automation, will experience only short-term productivity increases, and who, on the other hand, also stressed that "the biggest performance improvements come when humans and smart machines work together, enhancing each other's strengths" (Wilson & Daugherty, 2018, p. 1). In light of this, it seems reasonably to argue that the aforementioned points, in turn, imply that, in order to increase their business performance, businesses will likely increasingly implement automation technologies into their work environment within the next few years due to automation's augmentation potential. This, again, suggests that workers will also increasingly need the necessary technological and digital skills in order to work effectively with automation technology, thereby contributing to leveraging the full potential provided by successful human-machine collaboration. All in all, the aforementioned points strongly point towards an anticipated increase in the demand for technological and digital skills in the face of increasingly automated work environments.

In addition, the findings obtained by means of the interview study further suggest that not only may there be an anticipated increase in demand for certain technological and digital skills that enable workers to successfully collaborate with machines and to leverage the augmentation effect of automation, but also an expected growth in demand for those digital and technological skills that allow for the development of automation technology as well as for an adequate assessment, evaluation, and control of automation technology in order to ensure the responsible usage of automation technologies within the business environment. The finding that points towards an increase in demand for those technological and digital skills that enable individuals to ensure an appropriate and responsible usage of modern automation technologies presents an interesting insight that seems noteworthy to stress at this point as this point was not specifically and thoroughly addressed by the literature sources reviewed for the purpose of the extensive literature review conducted to yield relevant findings addressing the anticipated changes in the skill requirements of jobs within the context of automation. Thus, while various literature sources emphasized the expected increase in demand for technological and digital skills in order to engage with, interact, and work effectively with modern automation technologies (see e. g. Rainie & Anderson, 2017), the literature sources reviewed put no emphasis on the seemingly important technological and digital skills that allow for the adequate assessment, evaluation, control, and responsible usage of these technologies found by the qualitative research study. The fact that these skills seem to not be thoroughly acknowledged by extant literature when discussing the future skill trends and demand, in particular with regard to technological and digital skills, within the context of increasingly automated work environments suggests that this issue, albeit considered highly important as implied by the findings derived by means of the expert interviews, is not yet given the attention by scholars and researchers that it obviously deserves. In addition, the insight presented above also points towards the need for more in-depth or granular research in terms of the assessment or prediction of future skill requirements of jobs in order to obtain more data-rich and valuable insights, thereby contributing to the provision of the best possible skill demand forecasts that would be highly beneficial for various societal stakeholders as already argued in the introductory chapter of this thesis.

This being said, it may be concluded from synthesizing both the literature findings (see e. g. Vazquez et al., 2019; WEF, 2018) as well as the insights derived by means of the expert interviews that, generally speaking, there will likely be an increase in the demand for technological and digital skills due to the anticipated growth in the adoption and implementation of sophisticated automation technologies into the work environment.

However, while the overall findings obtained through both the interview study as well as the extensive literature review seem to show a clear pattern with regard to the future importance of and demand for technological and digital skills, some points concerning the interview study's findings require further clarification or attention and will be discussed in the following.

To start with, an important aspect that requires further attention relates to one of the statements provided by one interview respondent, who argued that it is essential to consider that not all technological and digital skills will be equally important in the future. This, in turn, implies that the literature findings, which rather consistently suggest that digital and technological skills will likely increase in demand within the context of job automation, seem to entail a generalization or an oversimplification of reality that should be seen critical, at least to a certain extent, within this context. In general, the findings derived from reviewing relevant literature sources commonly suggest that technological and digital skills will likely experience a demand within the next few years due to increasingly automated work environments (see e. g. Bughin et al., 2018; WEF, 2018). While this clear or obvious trend regarding the anticipated demand for technological and digital skills is consistently communicated by relevant literature sources reviewed in the realm of this work, only one study reviewed also pointed towards certain, even though slight, irregularities concerning the expected demand for skills pertaining to the category of technological and digital skills (see Bughin et al., 2018). In view of this, Bughin et al. (2018) found that, while still arguing for an anticipated increase in demand for both technological and digital skills in the context of automation, the need for distinct advanced technological skill varies. Nevertheless, while this insight may be an interesting finding that may, to a certain extent, influence the communicated general, clear trend in terms of technological and digital skills, this insight does still imply that all technological skills are expected to increase in demand in the context of automation, may it be to a stronger or lesser degree. However, the insight derived from the expert interviews clearly suggests that it can be expected that not all technological and digital skills will increase in demand, but that certain skills may stagnate or even see a decline in demand. This suggestion, in turn, also has important implications for the anticipated skill requirements of jobs. Hence, in view of the aforementioned points, it may be concluded that, even though both the literature findings along with the findings derived from the interview study commonly point towards a general increase in the demand for technological and digital skills, it is, nevertheless, important to stress at this point that it needs to be acknowledged that the conclusions drawn within the context of this work with regard to the anticipated future trend of technological and digital skills are, to a certain extent, generalized. Nevertheless, as already argued earlier, it may also be emphasized again that the objective of this thesis was to explore the general trends of and demand for skills, rather than provide a detailed and systematic overview of the distinct inconsistencies or irregularities identified in the overall findings. However, it was still considered noteworthy to mention within this context that inconsistencies or irregularities in terms of future skill trends and requirements may exist that should not be neglected in order to provide a more detailed account of how job automation is changing the skill requirements of jobs. In light of this, the points outlined above imply that further research may be necessary to achieve this goal of a more in-depth, data-rich, and detailed information relating to anticipated future skill trends, changes, and demand.

In relation to the aforementioned points, another aspect that should be looked at more clearly at this point relates to the future importance of STEM skills. While both the findings derived from the literature as well as several responses of the experts interviewed generally point towards a strong increase in the demand for STEM skills within increasingly automated work environments, it seems, nevertheless, noteworthy to mention within this context that the insights from both the literature as well as the interview findings also imply certain inconsistencies in terms of the overall expected trend of and demand for STEM skills. In view of this, one insight from the interview study suggests that this forecast or estimate of an expected increase in the demand for STEM skills should not be viewed as straightforward or obvious as commonly communicated. As stressed by one interviewee, the statement that STEM skills will likely increase in relevance and importance within the near future should be viewed with caution as this expected skill trend is based on a generalization that should be seen more critical. Thus, this indicates that such a generalization, as already indicated above, may oversimplify reality. This insight, in turn, suggests that this issue of generalization, when viewed critically, may mitigate this overall trend of an increase in STEM skills. In line with the aforementioned points, one literature source reviewed for the purpose of the literature review conducted in the realm of this thesis underlines this issue of potential generalization mentioned above (see FYA, 2017). As stressed by the FYA (2017), and consistent with the insight provided by the interview mentioned earlier, due to the prediction that even future job roles that are strongly based on science and mathematics, and hence, require a sophisticated level of STEM skills, will also demand a certain proficiency in skills pertaining to different skill categories, such as social and emotional skills as well as advanced cognitive skills. In view of this finding, the FYA (2017) concluded that the sole possession of well-developed STEM skills will not be sufficient to thrive in anticipated future work environments as other skills associated with different skill categories will be equally important. Hence, while the discussion provided above does not seek to contradict the general conclusion drawn from the overall findings that argues that demand for STEM skills will likely increase in demand within the next few years within the context of automation, the aforementioned points, however, still suggest that this may be an over-generalized finding that requires further attention. In view of this, it may be argued at this point that further research may be necessary in order to draw more specific conclusions regarding the future trend of STEM skills in the context of automation.

Finally, one last point that was considered important to acknowledge within this context relates to one of the findings from the interview study that suggests that, due to the increasing usage of automation technologies, highly advanced skills associated with the domain of technological and digital skills will be more and more required in the future in order to ensure the responsible, fair, and ethical usage of automation technologies within a business context. However, in one of the experts' view, such highly advanced skills seem to be not yet sufficiently available in the current skill market and therefore need to be further developed in order to meet the demand for such sophisticated skills. Hence, further research may not only explore or determine specific supply of and demand for the said highly advanced technological and digital skills, but may also explore suitable ways, for example with regard to education, that may close this potential skill gap that may be identified when investigating or determining the availability of those skills in relation to the demand for those skills. With regard to the points mentioned above, two literature sources cited within the context of the extensive literature review presented earlier in Chapter 2.4 also underline this argument put forward by the interview finding mentioned that suggests that, in terms of certain technological and digital skills, current supply seems not to sufficiently meet expected demand for these skills. As already noted earlier, Vazquez et al. (2019), for example, found that in spite of the importance of possessing digital skills in order to succeed in the future labor market, various employers argue that a significant proportion of workers do not appear to be prepared for the anticipated increasing demand for digital skills. Further, as also mentioned earlier, Curtarelli et al. (2016) noted that approximately 15% of employers propose that a substantial share of their employees is not sufficiently skilled in performing work tasks that include the usage of digital technologies, and that this finding point towards the presence of a digital skills gap within the workforce. In view of this, these literature insights cited, again, emphasize the above-mentioned obvious need for additional research to identify potential skill gaps within this context, as well as to derive important and valuable implications for closing the potential skill gap.

All in all, due to the expected increase in importance and relevance for workers to obtain or develop technological and digital skills in order to succeed in the envisioned future world of work that is expected to be increasingly characterized by the adoption and implementation of modern automation technologies into the workplace, it seems reasonably to defer from the interview study's findings that, even though not all interview respondents explicitly stated that they expect an increase in demand for technological and digital skills, thereby shaping the skill requirements of jobs, with some only having utilized expressions, such as "will increase in relevance" when discussing the future trend of technological and digital skills in the context of automation, skills pertaining to the category of technological and digital skills will likely increase in demand within the next few years. Hence, the findings obtained by means of the expert interviews seem to be consistent with the literature findings presented earlier that also, in general, argued for an expected increase in demand for those skills (see e. g. Bughin et al., 2018; WEF, 2018), which, in turn, is anticipated to considerably shape the skill requirements of jobs.

Systems skills

Further, the findings from the interview study addressing the category of systems skills that were presented in the preceding chapter imply that with the increasing adoption and implementation of automation technologies in the work environment, systems skills will also increase in relevance as, according to several interviewees, it is important for workers to not only understand the aspects and conditions associated with the working and functioning of automation technologies, but to also be sufficiently skilled to be able to relate all these aspects to the specific context, in which the human workers are collaborating with machines. This is also in line with the general definition of systems skills provided earlier (see Bakhshi et al., 2017). In view of this, the findings from the qualitative research study seem to not contradict the findings derived by means of the literature review that state that, due to an expected increase of automation in work environments, systems skills will likely grow in demand (Bakhshi et al., 2017; Rainie & Anderson, 2017). However, even though the findings from the interview study point towards the same future trend of the category of systems skills as identified in the literature, it should be stressed at this point that the wording used by the interview respondents that addressed the systems skills in their responses when talking about future skill needs merely point towards an increase in the importance and relevance of systems skills within the next few years. To say that the study's findings clearly point towards an overall increase in the demand for systems skills would be an exaggeration or even a contortion of the interviewee's responses. However, when the findings from the interview study are put in relation to the literature findings, then one could argue that there seems to be a certain upward trend regarding the future demand for systems skills as they are, to a certain extent, directly related to the degree of prevalence of automation in the work environment.

This being said, another point associated with this domain of systems skills requires further attention. As already indicated above, several experts that were interviewed in the realm of the interview study argued that an important part of systems skills relates to the proficiency of being sufficiently skilled to relate the aspects associated with the working and functioning of the technologies and machines that are implemented into the working environment back to the overall workplace context. The term "context" is an interesting aspect to mention as, as already argued earlier, the proficiency to take into account one's context and thus, to adequately emulate skills associated with taking certain contexts into account, seems to be incredibly challenging for even sophisticated automation technologies (Kosslyn, 2019). This, in turn, further strengthens the overall argument that systems skills will likely experience an increase in demand.

Lastly, another aspect noteworthy to mention within this context of systems skills relates to one statement provided by one interview participant of the qualitative research study, who argued that, even though stressing that there will likely be an increase in the relevance of systems skills due to increasingly automated work environments, there are not many people who, at present, have such systems skills due to the complex interplay of diverse skills that constitute systems skills. According to the respondent, this specific combination or interplay of distinct skills that make up systems skills are not sufficiently developed among many workers. This insight, in turn, suggests that, due to the insufficient development or proficiency of systems skills across the general workforce in combination with the expected increase in the demand for those skills, future supply of systems skills may not be able to meet future demand for systems skills, thereby potentially resulting in skill gaps. Thus, future research may explore or determine in more detail potential gaps between the supply of and demand for systems skills in order to contribute to an increased understanding and knowledge among various societal stakeholders that may valuably use this information to adequately prepare for and manage possibly emerging skill gaps. The subsequent section will discuss important implications within this context in more detail.

Overall, even though the responses provided by the experts do not explicitly state an expected increase in demand for systems skills, but rather reflect an overall increase in relevance and a growth in importance of systems skills, it may still be deferred from the interview study's findings that, based on the arguments provided by the experts within this context, skills pertaining to the category of systems skills will likely experience an increase in demand within the next few years. This, in turn, implies that this expected change in demand for systems skills will also likely be reflected in the skill requirements of jobs, shaping them accordingly. In view of this, the conclusion drawn from the interview study with regard to the future trend of systems skills seems to be consistent with the anticipated trend communicated by the findings obtained from the literature that also point to a likely increase in demand for systems skills that, in turn, will likely be visible in unfolding changes in terms of the skill requirements of jobs (see e. g. Bakhshi et al., 2017; Rainie & Anderson, 2017).

4.1.2 Skill Categories that are Expected to Decline in Relevance and Demand within a Job Automation Context

To continue, consistent with the findings derived from the literature, the findings that resulted by means of the analysis of the interview data also suggest that certain skill categories as defined in Chapter 2.4.2 are likely to decrease in relevance or demand within the context of job or task automation. In light of this, the key insights relating to each of those categories along with their meaning and interpretation will be discussed in the following.

Physical and manual skills

In terms of the skill category of physical and manual skills, the expert interviews carried out in the realm of the qualitative research study conducted in the realm of this thesis surprisingly did not yield very data rich insights that directly point towards the potential future trend of and demand for physical and manual skills. To be more specific, while none of the interviewees made direct statements concerning whether physical and manual skills are anticipated to decline or increase in the future within the context of automation, only two of the experts addressed these skills specifically in their responses without, however, providing clear statements regarding their anticipated future trend or demand. As already indicated, this is rather surprising as, in the literature, the domain of physical and manual skills is counted among the most cited skill categories within the context of skills that are expected to experience a decline in demand due to the fact that modern automation technologies will increasingly take over tasks that, to a large extent, require physical and manual skills (see e. g. Bakhshi et al., 2017; Bughin et al., 2018; Manyika, Lund, Chui et al., 2017; WEF, 2018).

This shortage of insights provided by the experts interviewed in terms of the anticipated future skill trend of physical and manual skills may be explained by the fact that the increasing automation of tasks requiring, to a large extent, physical and manual skills, which, in turn, points towards an expected decline in demand for skills pertaining to this skill category as argued earlier in Chapter 2.4 presenting the literature findings (see e. g. Bakhshi et al., 2017; Bughin et al., 2018; Manyika, Lund, Chui et al., 2017; WEF, 2018), was perceived as too obvious by the respondents, which, in turn, may have unconsciously refrained from discussing this topic in more depth or in a higher frequency. After all, one interview participant stated that, even though this statement was provided in a different context when addressing the future trend of learning skills, the expert himself did not explicitly mention the expected increase in the importance of learning skills as, according to the expert, due to the utmost importance of learning, it was just too self-evident to mention it at this point. Based on this, when applying or relating this kind of reasoning to the topic of physical and manual skills as discussed above, one may argue that, due to the apparent self-evident nature of an expected decline in the importance of physical and manual skills, the respondents unconsciously chose to not address this theme at a higher frequency or in more detail. However, it also needs to be stressed that this only presents an insinuation, and that this finding discussed above may be explained by various other factors not considered at this point.

Nevertheless, this being said, the two experts from the interview study, who addressed the anticipated future direction of physical and manual skills, both shared their excitement about automation technologies taking over more of the routine, repetitive, and often boring, exhausting, and drudge physical and manual tasks, while one respondent further stressed that the fact that automation will be increasingly taking over those tasks from human workers would mean that the workers will have more time to spend on more valuable work tasks in which they could, for example, utilize much more of their creative thinking skills. These insights, in turn, may imply that, while not directly referencing any clear trends regarding the possible decline or increase in demand for this skill category, the goal is to increasingly let machines carry out those work tasks that are largely based on physical and manual skills in order to enable human workers to spend more time performing tasks that are not only more valuable but that also require more of higher-level skills that machines are not yet able to adequately emulate. Hence, those insights may indicate that, in order to ensure an efficient and effective collaboration strategy between humans and machines, businesses may aim to increasingly automate those tasks that mainly require physical and manual skills easily done by automation technologies, such as robotics. This again, in turn, may suggest that, based on the arguments provided above, physical and manual skills are likely to decrease in demand within the next few years, thereby shaping the skill requirements of jobs accordingly. This reasoning would be in line with the conclusion drawn from the literature findings that suggests that, in general, physical and manual skills will likely experience a decline in demand within the coming years, and that this anticipated change is expected to be reflected in the skill requirements of jobs (see e. g. Bakhshi et al., 2017; Bughin et al., 2018; Manyika, Lund, Chui et al., 2017; WEF, 2018).

However, this being said, one of the interviewees shared an interesting insight that relates to the technical automation potential of automation technologies regarding the adequate emulation of physical and manual skills by stating that, as already outlined in the previous chapter, certain manual skills are still difficult to be emulated properly by automation technology. Within this context, the respondent specifically referenced skills related to finesse. This viewpoint is interesting in the sense that it potentially mitigates the literature findings that generally suggest that, even though the category of physical and manual skills is expected to remain a significant element of the future workplace and is anticipated to remain the largest skill category across all skill categories (Bughin et al., 2018), a clear downward trend is to be expected in terms of the demand for skills pertaining to this skill category of physical and manual skills within the context of increasingly automated work environments (see e. g. Bughin et al., 2018). Hence, this insight obtained by means of the expert interviews may indicate that, again, certain empirical forecasts regarding future skill trends and demand within the context of automation that directly shape the skill requirements of jobs are based on too vague generalizations that may eclipse or obscure certain noteworthy exceptions that have the power to alleviate certain forecasts or estimates, thereby underlining the necessity of adopting a more critical viewpoint when talking about the expected changes in the skill requirements of jobs. In view of this, even though the literature sources reviewed for the purpose of the present work commonly and strongly point towards a likely decline in the demand for skills pertaining to the category of physical and manual skills as a result of automation, one noteworthy literature finding still needs to be stressed at this point that, consistent with the above-mentioned insight derived from the expert interviews, reflects a certain inconsistency with regard to the overall expected skill trend of and demand for physical and manual skills within the context of automation. As argued by Bughin et al. (2018), even in the face of an expected general downward trend concerning the demand for physical and manual skills identified by means of their analysis, this identified likely downward trend is not anticipated to be visible in all sectors as, for example, within the US healthcare sector, the demand for gross and fine motor skills is predicted to grow by around 30 percent due to the assumption that an aging population fosters the need for work activities associated with, for instance, nursing and physical therapy (Bughin et al., 2018). However, as the finding reported by Bughin et al. (2018) was identified by the author of this thesis as the only finding that may potentially mitigate or weaken this, in general, consistent anticipated decline in demand for physical and manual skills commonly communicated by extant literature, it may still be concluded, as already indicated above, that, all in all, the literature findings strongly suggest an overall decrease in demand for physical and manual skills. Nevertheless, as both the interesting insight derived from the expert interviews along with the finding reported by Bughin et al. (2018) imply, further research may be necessary to provide a more granular or differentiated perspective of anticipated future skill trends of and demand for physical and manual skills in order to offer various societal stakeholders, such as businesses or educational institutions, the most valuable information that may influence their decision-making. In fact, it may be concluded from the aspects discussed above that future research should explore and seek to determine a more detailed, granular, and differentiated account of the future trend of and demand for each distinct skill category as outlined in Table 1 along with their associated skills or skill sets in order to provide the best possible decision-base that may be highly beneficial for various societal stakeholders. While this seems to be an important endeavor to be undertaken by future research, it, however, needs to be emphasized again at this point that the objective of the present thesis was to provide a general overview of anticipated skill trends and demand that are considered to ultimately shape the skill requirements of jobs within the context of increasingly automated work environments in advanced economies, rather than to provide an account of various irregularities or inconsistencies that may exist in terms of the anticipated trends and changes of, as well as demand for workforce skills.

Overall, while the literature findings demonstrate a clear downward trend in terms of the demand for skills pertaining to the category of physical and manual skills as a result of increasingly automated work environments, both the argument that the anticipated decline in the demand for physical and manual skills may not be visible in all sectors (Bughin et al., 2018) as well as the insight obtained by the interview study discussed above that implies that the expected downward trend in terms of the decline in the demand for physical and manual skills may not apply to each distinct skill pertaining to the category of physical and manual skills, imply that the anticipated decline in demand for physical and manual skills may also entail some exceptions or mitigations that need to be acknowledged within the present context. Nevertheless, as the present work has its focus on the general changes that are anticipated to occur in the skill requirements of jobs as a result of automation as already stressed above, it still seems reasonably to argue that the overall findings discussed above imply that physical and manual skills will likely experience a decrease in their demand, which, in turn, is expected to also be reflected in the changes occurring in the skill requirements of jobs. Again, it needs to be emphasized at this point that the central question asked in the realm of the present thesis does not inquire which kinds of skills will be, or which will not be required anymore from workers, but instead seeks to explore how, in general terms, the different skill categories as outlined in Chapter 2.4.2 as well as their associated skills will likely change not only in terms of their attributed importance and relevance as a result of increasingly automated work environments, but, more importantly, in terms of their anticipated future demand that, as already argued throughout this work, will ultimately shape the skill requirements of jobs.

Basic cognitive skills

To continue, similar to the findings regarding the future trend of physical and manual skills, the insights obtained by means of the expert interviews in terms of the expected future trend of skills belonging to the domain of basic cognitive skills do not suggest a very clear picture regarding their anticipated future demand as the findings do not entail much informative value concerning the expected future trend of this skill category within the context of automation. This, again, presents a rather unexpected finding as the literature findings obtained by the extensive literature review presented earlier clearly point towards an overall decrease in the demand for basic cognitive skills in the face of increasingly automated work environments (see e. g. Bughin et al., 2018). To illustrate the rather imprecise findings derived from the interview study within this context, one respondent stated that the word "decline" may not be the proper word to use in this context as, for example, reading skills will always, according to the respondent, remain an important skill to have. On the other hand, the same respondent also indicated that, even though reading skills will probably always be required of humans, modern automation technologies will become increasingly capable of adequately emulating basic cognitive skills, such as basic reading skills. This insight is also supported by one of the statements provided by another expert as thoroughly outlined in the preceding chapter. Those insights provided by the respondents, in turn, may imply that, in the face of the increasing automation of tasks that mainly require basic cognitive skills, those skills will likely decline in demand within the next few years. In addition, even though the interview study's findings that directly relate to the possible future trend of basic cognitive skills seem somewhat too sparse and insufficient in order to draw precise conclusions with regard to their overall future trend and demand, the findings derived from the interview study concerning the expected future demand for advanced cognitive skills that, as already argued above, strongly suggest an expected increase in demand for skills pertaining to the category of advanced cognitive skills may indirectly support the overall literature findings addressing the expected future trend of this skill category, which indicate that, in general, advanced cognitive skills will likely experience an increase in demand as a result of the increasing adoption and implementation of modern automation technologies into the workplace (see e. g. Bakhshi et al., 2017; Bughin et al., 2018; Cedefop, 2018; Manyika, Lund, Chui et al., 2017). As argued earlier in this thesis in Chapter 2.4.2, the literature findings imply that, within the coming years, the demand for basic cognitive skills will more and more decline as automation technology increasingly entails the necessary capabilities to properly emulate the skills pertaining to the skill category of basic cognitive skills, thereby effectuating a shift in the demand from basic cognitive skills towards advanced cognitive skills that even sophisticated automation technologies cannot emulate adequately (Bughin et al., 2018). In view of this, as argued above, the interview study's findings addressing the skill category of advanced cognitive skills generally suggest that, due to the difficulties for even modern automation technologies to properly emulate the skills pertaining to this skill category, advanced cognitive skills will increase in relevance within the next few years as automation may be taking over more of the tasks or jobs that, among others, mainly require basic cognitive skills that, as argued above, are much more easily emulated by automation technologies. Hence, the findings derived by means of the expert interviews imply that the tasks that remain untouched by automation will increasingly require those skills that automation cannot sufficiently emulate, such as advanced cognitive skills. These insights, in turn, support the literature findings by indicating that there will be a shift in the demand from basic cognitive towards more advanced cognitive skills (see e. g. Bughin et al., 2018), thereby likely effectuating a decline in the demand for basic cognitive skills. Thus, even though no direct and explicit statement may be made solely based on the interview responses given concerning how the demand for skills pertaining to this skill category may change in the next few years, thereby shaping the skill requirements of jobs, the findings still contain some information from which a conclusion regarding their trend may be drawn. Hence, in view of the aforementioned discussion, when taking into account not only the findings derived from the qualitative research study that relate to the expected future trend of and demand for both basic and advanced cognitive skills, but also the overall literature findings, then one could argue that basic cognitive skills will likely experience a decrease in their demand in the near future within the context of automation, and that the skill requirements of jobs will shift accordingly.

4.1.3 The Relevance of Diverse Skill Portfolios

In terms of the findings relating to the expected future importance for workers to possess a combination of diverse skills in the context of automation, the findings from the interview study seem to largely coincide with the literature findings presented earlier within this context. To be more specific, while it can be inferred from the interview study's findings that the combination of technological and digital skills, social and emotional skills, advanced cognitive skills, along with systems skills may be particularly helpful for workers to thrive in future work environments that are expected to be increasingly characterized by automation solutions, the literature findings similarly suggest that the combination of diverse skills, especially skills relating to the domains of technological and digital skills, social and emotional skills, as well as advanced cognitive skills, will become more and more important for workers within the context of increasingly automated work environments as this specific combination of skills is said to assist workers to succeed in the anticipated future world of work (Bughin et al., 2018; FYA, 2017; OECD, 2018; Riad, 2017; Vazquez et al., 2019). In view of this, the fact that the category of systems skills is missing from the literature findings that directly address the future relevance of specific skill combinations as a result of automation may be explained by the fact that, based on what can be derived from the extant literature reviewed for the purpose of conducting a thorough literature review within the realm of the present thesis, the domain of systems skills constitutes a skill category that is, compared with the other skill categories cited above, relatively seldomly addressed and explored by researchers that conduct research within this research field and topic. This issue of systems skills not being recognized in the same way as, for instance, cognitive skills or social and emotional skills in forward-looking studies addressing the implications of automation with regard to skill requirements of jobs may be attributed to the fact that, due to the variety and vagueness of definitions of systems thinking, "people get confused about what "systems thinking" means" (Linder & Frakes, n.d, p. 1.) and that notions including "interconnectedness" and "feedback loops", which constitute notions strongly associated with the concept of systems thinking, may be too overwhelming to be adequately grasped by individuals (Acaroglu, 2017). Nevertheless, as both the findings from the interview study as well as the literature review suggest, strong levels of systems skills are considered highly valuable for workers to obtain and to develop as a good proficiency in systems analysis and evaluation seems to be highly beneficial as they enable workers to work more effectively within increasingly complex and automated work environments. This argument is also highlighted by many prominent voices including Russel Ackoff, Peter Checkland, and Peter Senge (Rogers, n.d.), with the latter emphasizing the importance of systems thinking skills for developing a learning organization (Lennon, 2018). Thus, in order to make this concept of systems skills more widespread and prevalent, future research may address this concept more frequently, thereby potentially strengthening the recognition of this important skill category that it seems to, based on the findings presented throughout this work, ultimately deserve.

All in all, when taking together both the findings from the qualitative research study along with the literature findings in terms of the future relevance of certain skill combinations, a picture emerges that accurately reflects the distinct skill trends identified throughout this work and that are discussed above as skill categories expected to increase in importance or demand within the next few years due to an expected increase in the adoption and implementation of automation technologies into the work environment, thereby shaping the skill requirements of jobs in a substantial manner.

This being said, one interesting point that was mentioned by one of the interview respondents seems to be noteworthy to address in this context of the future relevance for workers to hold a diverse portfolio of distinct skills. As argued by the respondent, while acknowledging that it seems reasonable for people to argue that, in the face of continuous technological progress in the context of automation, STEM skills will likely increase in relevance in the next few years, "it is dangerous to argue that the only thing that counts in the future are STEM skills" (Interviewee 8) as, according to the interviewee, there are certain social and emotional skills, such as communication and leadership skills, that are equally important. Hence, this insight provided by the expert also underlines the conclusion derived from both the findings from the interview study along with the literature findings in that having a diverse portfolio of different skills is an important aspect to consider for current and future workers by suggesting that, even though one skill set is expected to increase in demand in the coming years, it seems dangerous to put too much emphasis on one skill category while, at the same time, disregarding others. In relation to the aforementioned points, another insight provided by one interview participant of the qualitative research study conducted in the realm of this thesis also seems worthwhile to acknowledge at this point. In view of this, while endorsing the relevance or importance for workers to be able to display strong levels of a variety of distinct skills in order to stay attractive in the future labor market within the context of increasingly automated work environments, and while especially referencing in this context the attractive combination of technological and digital skills along with social and emotional skills, the expert interviewed additionally implied that the so-called "people skills", such as communication skills and adaptability skills, are even more important to focus on as they are much harder to develop and learn compared to digital and technological skills. While this insight does not mitigate the anticipated increase in relevance and importance for workers to possess a diverse skill portfolio, it, nevertheless, entails some important implications that may be shortly acknowledged at this point. With regard to this and underling the insight provided by the interviewee, Opyt (2019) argued that, while also noting that social and emotional skills are much harder to measure than other skills, such as "hard skills", skills pertaining to the category of social and emotional skills are much harder to develop than, for example, hard skills. This, in turn, insinuates that, even though social and emotional skills are expected to be equally important as technological skills, the issue that social and emotional skills seem to be much harder to develop and train may promote skill gaps that, as will be discussed in more detail in the subsequent section, may have adverse implications for businesses. In relation to the aforementioned points, Eikenberg (2018) further interestingly argued that, while also stressing that social and emotional skills prove difficult to develop within organizations, thereby potentially inciting skill gaps, workplace cultures have an important role to play in order to make available the required levels of social and emotional skills. According to the author, workers should perceive that the organizational culture of their respective organizations approves of and promotes workers to utilize their valuable social and emotional skills (Eikenberg, 2018). Thus, the author suggests that it may not be the missing availability or lack in supply of those skills that may result in perceived skill gaps, but, in fact, the nature of the organizational culture that may or may not "allow those skills to shine" (Eikenberg, 2018, p. 1). Hence, the author argued that the required social and emotional skills may already exist within the organization, and that "it's time to make sure your culture allows them to come out" (Eikenberg, 2018, p. 1). While the above-mentioned implications may not directly contribute to answering the central research question of the present thesis, they were still considered to be worthwhile to discuss, albeit shortly, as the aspects outlined above may contain valuable information for businesses in terms of closing their perceived or potential skill gaps.

Finally, one last point within this context of skill combinations that seems noteworthy to discuss in more detail relates to one of the responses provided by one interviewee, who argued that, as the new profession of tomorrow will become increasingly complex, having a portfolio of hybrid skills will become increasingly important in this new era of automation. The focus in this statement lies on the term "hybrid skills", which is, according to various literature sources, an important concept to acknowledge within this research field of future workforce skills in the context of increasingly automated work environments driven by sophisticated automation technologies (see e. g. Sigelman et al., 2019; Vu et al., 2019). Sigelman et al. (2019), for example, argued that jobs are not only becoming increasingly complex, but also more hybrid in the sense that more and more jobs are becoming multi-disciplinary in nature as a result of the increasing adoption and implementation of modern automation technologies into the workplace, thereby requiring an increasing variety of distinct skills pertaining to different skill categories including digital and technological skills, advanced cognitive skills, as well as social and emotional skills (Ellis, 2019; Sigelman et al., 2019). As remarked by Rallyware (2019), "the complexity of jobs dictated by tech advancements and automation calls for similarly complex interdisciplinary skills" (Rallyware, 2019, p. 1). In view of this, a hybrid job role can be described, according to Sigelman et al. (2019), as being more complex, more multi-disciplinary, and as demanding more diverse skills from various fields or disciplines compared to traditional job roles. In light of this, while stating that hybridization is increasingly becoming a mass phenomenon, Sigelman et al. (2019) further argued that hybrid jobs are not only growing at a much faster pace than traditional job roles, but also entail a much lower susceptibility to automation due to their nature. More specifically, findings show that hybrid job roles are expected "to grow twice as fast as jobs overall" (Sigelman et al., 2019, p. 6), thereby representing the "fastest-growing sections of the jobs market" (Sigelman et al., 2019, p. 10), and entail a much lower probability of being automated compared to more traditional job roles due to the fact that hybrid job roles are not only less likely based on routine, repetitive work tasks, but also demand more higher-order skills and inherently human skills including judgement, creativity, collaboration, problem-solving, and analytical thinking skills than traditional job roles (Sigelman et al., 2019). As illustrated by the findings from both the interview study and the literature review, those skills cited above all constitute skills that prove difficult, or nearly impossible, for even sophisticated automation technologies to emulate properly. Thus, in view of the points discussed above, the concept of hybrid skills and their expected growing need as well as future importance for workers to have in order to succeed in the anticipated future world of work strongly underlines the findings discussed above that suggest the growing relevance and importance for workers to obtain or develop a valuable portfolio of diverse skills or skill sets.

These insights discussed above relating to and pointing towards an expected increase in demand for hybrid skills within the context of increasingly automated work environments, thereby underlining the argument of the importance for workers to obtain or develop a diverse portfolio of skills, are also strengthened by some of the findings derived from the literature sources reviewed for the purpose of the present work. More specifically, while the FYA (2017), for example argued that workers will need to obtain or develop a diverse portfolio of different skills in order for them to succeed in the future world of work, Tytler et al. (2019) argued for an expected increase in the relevance for workers to hold cross-disciplinary skills as workers will be increasingly required to work throughout different disciplinary fields. While the latter argument may not directly point towards an increase in the prevalence of hybrid job roles as argued above, it, nevertheless, strongly suggests that workers, in general, are expected to be increasingly proficient in a wide range of skills pertaining to different skill categories in order to succeed in the anticipated future world of work increasingly characterized by automation and complexity. Lastly, the literature findings cited above are also underlined by Riad (2017), who argued that, while stressing that certain skills pertaining to distinct skill categories according to the skill classification outlined in Table 1 will be equally relevant in the future, thereby, according to the author of the present thesis, also emphasizing the anticipated future importance of cross-disciplinary or hybrid skills, future jobs will "marry science and art, so that humans can work with machines and not against them" (Riad, 2017, p. 18). While Riad (2017) may not have directly referenced the anticipated increase in hybrid job roles demanding hybrid skills as argued above, Riad's (2017) insight, nevertheless, implies that due to the increasing complexity and interdisciplinary of skills required for future job roles, cross-disciplinary or hybrid skills will also increase in importance and relevance within the next few years. This, in turn, again, strengthens the conclusion drawn from both the interview findings as well as the findings derived from the literature that suggests that there will be an increase in the demand for workers to possess a diverse portfolio of different skills pertaining to distinct skill categories in order to succeed and thrive in future anticipated work environments.

4.1.4 General Points That Need Further Attention and Clarification

After having discussed each key theme that directly relates to answering the central research question of the present thesis, the following discussion will continue by outlining some important aspects or points that require further consideration and acknowledgement before continuing with concluding this discussion section.

In view of this, an important aspect that needs to be acknowledged at this point relates to the overall clarity concerning the anticipated future skill trends and changes that are considered to inevitably shape the skill requirements of jobs within the context of increasingly automated work environments in advanced economies. To be more specific, while the findings derived from the literature reviewed for the purpose of this thesis generally convey a rather clear and obvious picture with regard to the expected changes in the skill requirements of jobs due to automation (see Table 2 for an overview of the skill trends identified), the findings and insights derived from the interview study that was carried out as part of this work in order to enrich and supplement the literature findings seem to mitigate, at least to a certain extent, the rather clear image or scenario commonly communicated by various literature sources regarding the changes in the skill requirements of jobs that are expected to take place within the next few years. To illustrate this apparent incongruity, while various studies that were cited within the context of the literature review presented earlier commonly made clear statements with regard to the anticipated future changes in skill requirements by utilizing words or expressions that typically convey a clear future scenario, such as "will decline in demand" or "will increase in demand" when referring to certain future skill trends (see e.g. AIG, 2018; Bakhshi et al., 2017; Bughin et al., 2018; Manyika, Lund, Chui et al., 2017; Tytler et al., 2019; Vazquez et al., 2019; WEF, 2018), the interview participants mostly used verbal expressions, such as "will increase in importance" or "will increase in relevance", when being asked about their viewpoints concerning future skill trends that are expected to substantially shape the skill requirements of jobs. Hence, the findings derived from the expert interviews seem to, based on the wording or expression used in the responses given by the participants, weaken or mitigate the overall clear or strong picture or scenario communicated by extant literature with regard to anticipated future skill trends and changes shaping the skill requirements of jobs in the context of automation. On the one hand, this may indicate that the literature findings seem to convey an overall picture in terms of future skill changes and demand that may be based on generalizations and even an oversimplification of reality. Hence, it is important to acknowledge that the overall skill trends outlined based on the literature reviewed may oversimplify reality as certain skill requirements of a given job may always deviate from general trends identified within this context. Thus, when speaking about expected future skill trends, changes, and demand within the context of automation, one should always have in mind that many forecasts may be based on generalizations that may depict an oversimplification of reality. On the other hand, it is important to acknowledge that the scope of the interview study was rather small with eight interview participants in total, which, in turn, as will be also addressed later in this section, may mitigate the generalizability and overall relevance or significance of the study. Nevertheless, the fact that the interview participants mostly utilized expressions in their responses that seem to be weaker than the conclusions drawn by the scholars and researchers cited in the realm of the literature review in Chapter 2.4.2 may still, as argued above, contain some informative value that should not be entirely neglected at this point.

This being said, it is important to emphasize that, even though the findings derived from the qualitative research study entail some insights that may be interpreted with a certain amount of caution or critique, the findings derived from the interview study should not be interpreted too critically as they still are mostly consistent with the literature findings in answering the central research question of this thesis as interpreted and concluded by the researcher as discussed above. In addition, it is also important to stress that certain literature sources also used verbal expressions or wording when addressing or discussing anticipated skill requirements of jobs that seem to be equivalent with the degree of conviction and clarity of most of the responses provided by the interview participants. In other words, certain literature sources reviewed for the purpose of this work also put forward statements and verbal expressions that are in line with the ones expressed by various interview participants in terms of the reflected clarity and conviction concerning anticipated changes in the skill requirements of jobs. Further, based on the literature review conducted within the realm of this work, not all literature findings seem to be free of inconsistencies or irregularities regarding expected changes in the skill trends, and thereby skill requirements of jobs (see e. g. Bughin et al., 2018).

However, even though some inconsistencies, irregularities, or exceptions seem to exist based on the findings derived from the literature, the point here is to argue that the general conclusions drawn by extant literature with regard to anticipated changes in the skill requirements of jobs and the overall picture that is conveyed by the literature sources reviewed for the purpose of the literature review outlined earlier still reflect a high degree of clarity and conviction regarding the expected future changes in the skill requirements of jobs, while the insights derived from the interview study point towards the necessity of being a little bit more cautious or critical when talking about certain future scenarios in the context of future skill trends and changes brought about by automation. In view of this, it also needs to be emphasized again that forward looking studies are typically characterized by entailing a certain degree of uncertainty (Patscha et al., 2017). Thus, the expressions or statements provided by the interview participants that seem to convey a certain amount of cautiousness regarding the future changes in the skill requirements of jobs, may reflect exactly this uncertainty that, as already argued in the beginning of this thesis, constitutes a common element when conducting forward looking studies. In view of this, what seems to be certain and where the findings from both the interviews and the literature agree is that certain tasks or jobs that are associated with specific skill requirements can easily be automated, while others prove much more difficult to automate. Based on this, as already argued above, it seems reasonably to defer and argue that some work tasks requiring certain skills will become increasingly important for human workers to carry out as automation technologies do not have the required capabilities to perform these tasks that are based on certain skills or skill sets. However, the expectations regarding future skill trends that are anticipated to unfold within the near future, thereby shaping the skill requirements of jobs, still entail a certain degree of uncertainty. This, again, is illustrated by the responses provided by the interview participants as some responses clearly imply certain future skill trends, while other responses seem to be more difficult to interpret in that sense. Nevertheless, as already argued earlier, even though some responses require a higher interpretive task from the researcher as they are not specifically addressing clear future trends based on the wording or verbal expressions used, they, however, may still entail important implications regarding future skill requirements, especially when the interview findings are viewed in combination with the findings derived from the literature as already remarked earlier. Notwithstanding, as already illustrated and thoroughly discussed throughout this section, both the findings derived from the literature as well as the insights obtained by means of the expert interviews still point towards certain skill trends shaped by automation that are expected to effectuate changes in the skill requirements of jobs, and which will be summarized shortly.

4.1.5 Limitations and Future Research

Further, some limitations in terms of the overall findings derived from both the literature as well as the interview study should be acknowledged at this point that may affect the conclusions drawn from the findings.

First of all, it is essential to stress that, as already indicated above, due to the limited number of study participants that amounted to eight interviewees in total that participated in the qualitative research study conducted within the realm of the present thesis, no generalizations of the findings obtained by means of the expert interviews can be made. However, even though the findings obtained by the interview study demonstrated some irregularities and inconsistencies compared to the findings derived from the literature, these are rather minor, and the conclusions drawn from the interview study's findings largely coincide with the findings derived from the extensive literature review conducted as part of this work. Hence, even though no generalizability solely based on the interview study's findings may be given, when combined with the findings derived from the literature, an overall consistent pattern emerges, albeit with some noteworthy exceptions as noted earlier, from which a higher degree of generalizability may result.

In addition, it is also important to note that, in line with the social constructivist worldview (see e.g. Creswell & Poth, 2016), according to which individuals try to obtain an understanding of their world and "develop subjective meanings of their experiences" (Creswell & Poth, 2016, p. 20), the conclusions drawn from the findings from both the insights derived from the qualitative research study as well as the findings obtained by means of the literature review merely reflect subjective interpretations due to the interpretive, constructivist stance exhibited by the scholars and researchers cited in the realm of the literature review, the participants chosen for the interview study, as well as the researcher herself when investigating, discussing, or interpreting the phenomenon at hand. As a result, interpretations and conclusions may contain some subjective biases that may influence the outcome of the interview study as well as the conclusions communicated and conveyed by extant literature.

Moreover, another limitation that should be pointed out that concerns the literature analysis conducted in the realm of this thesis relates to the number of studies reviewed for this process. In view of this, even though the researcher tried to the best of her ability to include a portfolio of different relevant and timely studies that adequately reflects the variety of findings relevant for providing a coherent answer to the central research question of the present thesis into this review in order to maximize the information and knowledge obtained through this literature analysis, it nevertheless should be emphasized that other sources concerning future skill trends and changes in the context of automation may exist that were not included in this review but may still provide valuable information with regards to the future of skills. Nevertheless, it should also be stressed at this point that, due to the adequate scope and quality that are perceived to be given in the researcher's viewpoint in terms of the literature reviewed for the purpose of the present thesis and answering the central research question, the researcher is confident in arguing that the overall picture that emerges from the literature review with regard to anticipated changes in the skill requirements of jobs due to automation is highly likely to reflect the overall depth and complexity of the nature of extant literature that addresses this research field of future skill trends and demands within the context of increasingly automated work environments.

Further, as already argued in the beginning of this thesis, it is important to stress once again that the findings in terms of the anticipated changes in the skill requirements of jobs obtained through both the extensive literature review as well as the subsequent qualitative research study do not provide any sector-specific information with regards to future skill trends and changes.

Rather, this work sought to provide relevant and timely information regarding general skill trends that are expected to unfold within the next few decades within the context of increasingly automated work environments. However, as, for instance, certain stakeholders may base their decision-making on the outcomes of this work, it is essential to forecast and assess future skill trends and changes as specific and precisely as possible in order to enable different societal actors to make accurate and informed decisions with regard to, for example, investments in training as well as to avoid or impede potential mismatches between skill supply and demand (Patscha et al., 2017). In addition, within this context, Chang and Huynh (2016) argued that, in order to obtain and develop an adequate understanding of the anticipated changes in the skill requirements of jobs within the context of automation, a sector-specific approach is needed as not every sector is equally affected by modern automation technologies. Nevertheless, due to the limited scope of the present thesis, it was refrained from providing detailed sector-specific information regarding anticipated changes in the skill requirements of jobs. Besides, even though the effects, changes, and challenges brought about by automation with regard to future skill trends and demand may vary depending on industry sector (see e. g. Chang & Huynh, 2016; Hawksworth et al., 2018), the high likelihood that the effects and implications of automation will be visible across a wide range of occupations that may span a wide range of different sectors (see e. g. FYA, 2017; Manyika et al., 2017), implies that, even though no sector-specific analysis is provided, the findings yielded within the context of this work still entail an informative value with regard to the general trends and changes expected to occur within the context of skill requirements of jobs.

Furthermore, even though some literature sources cited in the realm of the literature review presented earlier provided specific timeframes with regard to when the changes that were explored by the researchers in terms of the skill requirements of jobs in the context of automation are expected to likely unfold or emerge (see e. g. Bakhshi et al., 2017; Bughin et al., 2018; FYA, 2017), the findings derived by means of the qualitative research study conducted as part of the present thesis do not suggest an explicit timeframe during which the changes discussed by the interview participants may potentially unfold or emerge. This may simply be due to the difficulty of determining an adequate timeframe during which the changes explored may potentially unfold. In addition, within this context, the issue of uncertainty, again, plays an important role as every phenomenon that is explored in a forward-looking manner entails this certain degree of uncertainty as already argued earlier (Patscha et al., 2017).

However, time is argued to be an important factor as the more rapidly automation occurs in the workplace, the more disruptive it will be (Muro et al., 2019). Further, as argued by Delisle (2019), the absence of a specified timeframe can cause certain methodological issues in terms of the respective study and the resulting findings should therefore viewed and interpreted with caution (Delisle, 2019). In view of this, the issue of no set time horizon that may act as a frame for the changes under investigation in the present work may potentially bias the findings as well the conclusions drawn from the qualitative research study. Nevertheless, as identified from the extensive literature review outlined earlier, the changes that are expected to unfold in terms of the skill requirements of jobs as a result of increasingly automated work environments are considered to happen sooner rather than later. In fact, some even argued that the future of work is already here (see e. g. Capita, 2019; Russo, 2020). This, in turn, implies that, even though some literature sources cited in Chapter 2.4.2 provided a specific time horizon as a basis for their research that may influence the study's outcome, the provision of a concrete timeline seems to be of lesser importance than the actual conclusions drawn from both the literature findings as well as the findings derived from the interview study that argue that certain changes in the skill requirements of jobs brought about by automation seem to be highly imminent or, as some literature sources imply, are already happening (see e. g. Bughin et al., 2018; Capita, 2019; Russo, 2020). This not only underlines the importance and urgency of exploring this phenomenon, but also justifies the exploration of this phenomenon even though no specific time horizon may be available on which the expected changes may be based on. Based on the aforementioned points, for the purpose of the interview study conducted in the realm of this work, no specific time horizon was determined. Rather, certain expressions, such as "in the near future" or "within the coming years", were utilized in order to not only limit the anticipated changes to a certain timeframe, but to also signal that the expected changes in the skill requirements of jobs as a result of increasing automation are anticipated to be happening sooner rather than later. All in all, while it is acknowledged in this context that the timeline set in order to explore the topic at hand may have a certain influence on the changes that are expected to unfold in the near future as well as their scale and scope, thereby potentially affecting the response provided to answer the central research question of this thesis, the findings nevertheless imply that there will be certain changes in the skill requirements of jobs that are anticipated to unfold within the next few years, and which have important implications that will be further discussed shortly.

Overall, while the present work may not be without some limitations as outlined above, the findings derived from both the literature review as well as the interview study still generated some rich insights that may contain valuable information that may be used for the decision-making processes of a variety of stakeholders including current and future workers, businesses, as well as educational institutions. Implications for a number of societal stakeholders will be, among other aspects, discussed in the subsequent section.

In terms of possible future research areas, the discussion provided above already introduced and highlighted various areas that may be explored by future research. Nevertheless, one additional potential area for future research that relates to the anticipated changes in the skill requirements of jobs as a result of automation that were explored throughout this thesis was considered important to acknowledge at this point. As argued by the WEF (2020), the changes brought about by the ongoing global COVID-19 pandemic have intensified the lasting changes already caused by the fourth industrial revolution. As a result, the fourth industrial revolution is experiencing increased levels in terms of its velocity and depth (WEF, 2020). In view of this, according to the WEF (2020), businesses are planning to advance not only the digitalization of distinct work processes, learning, and extension of remote work, but also the automation of work tasks throughout the respective organization (WEF, 2020). Thus, future research may explore how the dual impact of both automation within the context of the fourth industrial revolution characterized by ongoing technological change and the current global pandemic are altering and shaping jobs, tasks, and skills within the coming years.

4.1.6 Conclusion of the Discussion Section

In view of the points presented and discussed throughout the present and preceding chapters, some concluding remarks will be provided in the following before continuing with the section outlining important implications that can be inferred from the findings and insights presented in the present work.

All in all, the synthesis of the findings derived from both the qualitative research study in the form of expert interviews as well as the literature review outlined in Chapter 2.4.2 yielded some valuable insights and information, based on which the central research questions of the present thesis can be answered. As illustrated above and throughout this work, the increasing adoption and implementation of modern automation technologies into the work environment within the context of advanced economies are expected to effectuate certain changes in the demand for specific skills pertaining to certain skill categories, which, in turn, are anticipated to shape the skill requirements of jobs. More specifically, as concluded from the overall findings presented in the realm of this thesis, while some skill categories along with their associated skills are expected to increase in demand, others are expected to decline in demand, thereby changing the skill requirements of jobs accordingly. As discussed, argued, and illustrated throughout this chapter, the overall conclusions drawn from the synthesis of both the findings derived from the literature as well as the findings obtained by means of the expert interviews with regard to how job automation is changing the skill requirements of jobs are, when taking a general viewpoint and when neglecting the identified irregularities and inconsistences as they were not the focus of the present work as already argued earlier, consistent with the anticipated skill trends already presented earlier in Table 2 within the context of Chapter 2.4.2 that provided an extensive literature review of anticipated skill trends, changes, and demand within the context of increasingly automated work environments. Based on this, the reader may at this point be referred back to Table 2 that provides an overview of the anticipated future skill trends that are considered to reflect the expected general changes in the skill requirements of jobs as concluded by this thesis. Nevertheless, for the purpose of practicality, Table 2 is, again, integrated into the present section as this was considered by the researcher to complete the discussion section, thereby hopefully contributing to the reader's overall understanding of the final conclusions drawn with regard to the central research question of the present thesis.

Table 4: Anticipated Future Skill Trends and Demand

Decline	**Growth**
▪ Physical & manual skills ▪ Basic cognitive skills	▪ Technological & digital skills ▪ Advanced cognitive skills ▪ Social & emotional skills ▪ System skills

Sources: AIG (2018); Bakhshi et al. (2017); Bughin et al. (2018); Cedefop (2017); Cedefop, (2018); FYA (2017); Manyika, Lund, Chui et al. (2017); OECD, 2018; Oschinski & Wyonch (2017); Rainie & Anderson (2017); Riad, 2017; Tytler et al. (2019); Vazquez et al. (2019); WEF (2018)

In view of the aforementioned points and as already highlighted above, it is important to stress at this point once again that the information communicated through Table 2 reflects the general skill trends and changes expected as a result of automation, thereby neglecting some exceptions, minor irregularities, or inconsistencies identified and discussed throughout this section that, as already emphasized above, may be further explored by future research. Hence, even though certain irregularities and inconsistencies between the findings from both the literature as well as the qualitative research study could be identified, it was, nevertheless, concluded that, generally speaking, the results point towards certain trends in the expected future demand for skills that, even though based on a more generalized view, have important implications for the skill requirements of jobs within the context of advanced economies. In particular, it may be argued that, based on Table 2, while skills pertaining to the categories of physical and manual skills along with basic cognitive skills are expected to become of lesser prevalence in terms of the requirements to perform a given job role, skills associated with the categories of advanced cognitive skills, social and emotional skills, technological and digital skills, as well as systems skills are anticipated to become much more prevalent in the general skill requirements demanded to perform a specific job role. In addition, the insight derived from the overall findings that argues for the increasing demand for holding diverse portfolios of different skills pertaining to distinct skill categories that are expected to increase in demand within the next few years also underlines and supports the aforementioned expected changes in the skill requirements of jobs. In a more general vein and in relation to the aforementioned points, it may be further concluded that the overall findings in terms of anticipated future skill trends and demand strongly point towards not only anticipated changes and shifts in the general skill requirements of jobs, but also towards an increase in the importance of and demand for higher-order skills as well as complex inherently human skills. In other words, the overall findings do not just suggest that workers will need simply different kind of skills in order to thrive in the anticipated future world of work increasingly characterized by automation, but that they will also increasingly need higher and more advanced skills. This, again, has important implications for various societal stakeholders as will be further discussed in the subsequent section.

To sum up, while it needs to be acknowledged that the conclusions drawn from the overall findings presented and discussed in this work may always entail a certain degree of uncertainty, the overall findings and insights, nevertheless, strongly suggest that automation is effectuating certain changes in the demand for skills within a work and business context that are expected to directly shape the skill requirements of jobs correspondent to the information provided above and in Table 2. These anticipated changes, however, may also bring about certain challenges for various stakeholders as not only indicated by various literature sources cited in the realm of the literature review conducted as part of this thesis, but also noted by several experts interviewed in the realm of the qualitative research study as outlined in Chapter 3.4. The following section builds on this insight by outlining a number of aspects that seem worthwhile to discuss in the context of expected changes in the skill requirements of jobs as a result of automation.

4.2 Practical Implications

As indicated earlier, sophisticated automation technologies, such as artificial intelligence and modern robotics, potentially entail significant benefits and opportunities for businesses including increased productivity and the possibility to achieve competitive advantage (Manyika et al., 2017). In general, the potential for economic development and progress provided by modern automation technologies seems to be remarkable (Servoz, 2019). However, as technological advances have the potential to substantially transform the boundaries between the work tasks and activities carried out by human workers and those executed by sophisticated automation technologies, global labor markets are expected to experience significant changes (WEF, 2018). In particular, as it is expected that automation will effectuate a substantial structural change in terms of the task content of jobs across advanced economies, the skill requirements of jobs impacted by automation that workers will face will also experience significant changes as discussed thoroughly throughout this thesis (see e. g. Manyika et al., 2017; Manyika, Lund, Chui et al., 2017; Nedelkoska & Quintini, 2018; Patscha et al., 2017; Servoz, 2019; Vazquez et al., 2019; WEF, 2018).

With regard to this, the anticipated changes in the task content of jobs along with the expected changes in the skill requirements of jobs impacted by automation will result in substantial challenges faced by a large number of workers and businesses (Bisello et al., 2019; Servoz, 2019; Vazquez et al., 2019; WEF, 2020). This is also underlined by Lamb et al. (2018), who argued that, while the increasing adoption and implementation of automation technologies may provide substantial benefits and opportunities including enhanced productivity and competitiveness, they are also expected to produce various challenges for workers and businesses alike (Lamb et al., 2018). For example, as illustrated earlier, it is anticipated that the adoption and implementation of modern automation technologies will make a certain number of skills obsolete whilst increasing the relevance and importance of other skills (Cedefop, 2018). Skills obsolescence refers to the situation where the skills that were previously deployed in a given job are no longer demanded or have lost their relevance and importance (Cedefop, 2018). As remarked by the D2L Corporation (2018), an increasingly dynamic skills market in the context of rapid and ongoing technological change implies that relevant skills are rendered increasingly obsolete, which, in turn, necessitates continuous training and development (D2L Corporation, 2018). In view of this, Patscha et al. (2017) emphasized that matching skill supply and demand across labor markets in the context of structural change brought about by automation presents a key challenge. According to Patscha et al. (2017), in order for societies to maintain overall prosperity and competitiveness, it must be ensured that workers will hold the skills needed for them to thrive and prosper in future labor markets. As argued by the WEF (2020), an employee's long-lasting effectiveness and productivity levels are, to a substantial extent, defined by the employee's proficiency in terms of their skills and competencies. Further, as stressed by the WEF (2020), fully seizing the opportunities and benefits resulting from the adoption and implementation of modern automation technologies is often impeded by skill shortages (WEF, 2020). As argued by the WEF (2020), skill gaps within labor markets along with difficulties in attracting suitable talent constitute significant barriers to the successful and effective adoption of automation technology. With regard to this and according to the WEF (2020), skill shortages are much more pronounced within emerging job roles, such as artificial intelligence and machine learning specialists. In relation to this, Sigelman et al. (2019) stressed that the increasing hybridization of job roles and required skills are likely to intensify or aggravate skill gaps and to render "existing talent supply pipelines obsolete, or even irrelevant" (Sigelman et al., 2019, p. 18). In view of the points mentioned above, Shook and Knickrehm (2018) found that, although over 50 percent of the business leaders asked in the realm of the survey conducted by the authors acknowledged the issue of skill shortages as one of the main workforce challenges, merely three percent of the respondents stated that they are planning to substantially enlarge investments in specific training programs within the next few years (Shook & Knickrehm, 2018). In relation to the aforementioned points, Allas et al. (2019) stressed that the increasing adoption and implementation of automation technologies will likely result in skill mismatches if businesses will not adequately prepare and manage the changes and shifts in the skill requirements of jobs caused by automation. As noted by Cedefop (2018), skill mismatch refers to situations, in which the supply of and the demand for skills differ. For example, skill mismatch relates to the occurrence when the skills possessed by individuals do not adequately fit the requirements of their jobs (Cedefop, 2018). While labor markets are imperfect and thus, mismatches in skills do exist to a certain extent, extreme cases of skill mismatch may have detrimental economic and social consequences (Cedefop, 2018). For instance, as stressed by Ceemet (2018), a mismatch between the skills required and the skills that are available may result in a substantial decrease of a company's competitiveness. Further, a lack in relevant skills may impede an economy's creation of wealth, thereby jeopardizing the maintenance of high social standards (Ceemet, 2018). Further, according to Ovanessoff et al. (2018), not only are economies at risk of losing a substantial amount of money in terms of the cumulative growth offered by sophisticated automation technologies if they are not able to meet the demand for future skills, but there's also the risk of increased levels of unemployment along with enhanced income inequalities when future skill demand is not being met. Overall, as sophisticated automation technologies, such as artificial and robotics, are transforming the nature of jobs and altering the skill requirements of jobs, skill gaps are expected to increase within the context of the fourth industrial revolution (Milano, 2019).

The points highlighted above clearly illustrate that the anticipated changes in the skill requirements of many jobs pose a key challenge in the context of this new age of automation (Bughin et al., 2018). In reference to this prevailing skills challenge brought about by automation, Bughin et al. (2018) remarked that "the stakes are high" (Bughin et al., 2018, p. 68). In this regard, the researchers stressed that a workforce armed with the relevant and necessary skills required to render the adoption and implementation of automation technologies into the workplace effective and productive will enable companies to reap valuable benefits including increased productivity growth and to empower workers to leverage their full potential (Bughin et al., 2018). However, failing to adequately meet the anticipated future skill needs may not only have potential negative effects for companies, such as impeded business performance, but also for individual workers and society as a whole given the potential risk for wage stagnation or reduction and rising inequalities (Bughin et al., 2018). With this in mind, the anticipated changes and challenges may result in a new era of good work and jobs provided that these transformations are managed reasonably and adequately (WEF, 2018). However, if managed badly, they may exacerbate the risks of broadening skill gaps and increased inequalities (WEF, 2018).

In light of this, an important implication that may be deduced from the findings and insights derived from both the literature as well as from the qualitative research study conducted in the realm of this thesis relates to the importance of effectively managing the anticipated changes and challenges effectuated by job automation in terms of future skill trends as argued above in order to ensure that the overall impact of advanced automation technologies associated with the current wave of automation will be positive (Patscha et al., 2017; Servoz, 2019). In this regard, according to various voices within the academic and scholarly literature (see e.g. Arnold et al.; 2018; Patscha et al., 2017), the anticipated changes and challenges described earlier necessitate a comprehensive policy approach that, on the one hand, supports the potential and possibilities provided by automation, and, on the other hand, simultaneously assists workers to obtain and develop the relevant skills required to succeed in work environments increasingly characterized by automation (Arnold et al.; 2018; Patscha et al., 2017). As stressed by McKay et al. (2019), a human-centric approach to automation is required in order to effectively manage the potentially disruptive effects brought about by automation. Overall, the dynamics, changes, and challenges in terms of the anticipated future skill trends and demands discussed within the realm of the present thesis entail a number of noteworthy implications for various stakeholders that will be outlined in the present section.

In view of this, based on the arguments provided above, the following discussion will provide a number of valuable action measures and efforts that various societal stakeholders including organizations, individual workers, education providers, and policy makers need to consider when aiming to take full advantage of the potential of automation while simultaneously seeking to prevent the dangers and manage the challenges associated with the anticipated changes in the skill requirements of jobs as a result of automation (Bughin et al., 2018; Manyika et al., 2017; WEF, 2018). As the subsequent discussion will illustrate, a variety of stakeholders including individual workers, business leaders, education providers, and policy makers all have an important role to play in managing the challenges associated with the anticipated changes in the skill requirements of jobs that are expected to emerge as a result of this new wave of automation within the context of the fourth industrial revolution (Bughin et al., 2018; Manyika et al., 2017; Manyika, Lund, Chui et al., 2017; WEF, 2018).

4.2.1 Reskilling & Upskilling

In view of the anticipated changes in the skill requirements of jobs resulting from automation presented above, Manyika, Lund, Chui et al. (2017) emphasized that offering job training and assisting workers to acquire new relevant skills constitute an essential challenge in the years to come. In line with this, the World Economic Forum (WEF, 2018) pointed out that, while, on the one hand, a number of job roles predicated on manual and routine-based work are expected to experience a decline in demand, and, on the other hand, other job roles are anticipated to increase in relevance and demand, a central issue that will concern all industries constitutes the necessity to reskill affected workers in order for them to shift from jobs characterized by an anticipated future decline towards those job roles that likely see a growing demand (WEF, 2018). Consistent with this, respondents surveyed in the realm of the analysis concerning the future of work conducted by the World Economic Forum (2018) expect that, within the next few years, more than half of all employees across an extensive range of industries and geographies will need to undergo substantial reskilling and upskilling (WEF, 2018). In view of this, the term "upskilling" means "taking the essence of what employees do and improving it – helping them become more advanced, more gifted at what they do" (Rahilly, 2020, p. 2) and basically assisting workers to "gain new skills to help in their current roles" (Ellingrud et al., 2020, p. 2), whereas "reskilling" refers to training individuals in something new so that they develop the skills needed to perform different or completely new job roles (Ellingrud et al., 2020; Rahilly, 2020). Further, in line with the arguments provided by the WEF (2018), Bakhshi et al. (2017) emphasized that investments in skills should be at the core of any long-term strategy for adapting to structural change. In addition, according to Manyika et al. (2017), one of the most critical factors to ensure successful implementation of automation into the workplace constitutes the necessity to prepare and develop the workforce to work alongside technology in a complementary manner (Manyika et al., 2017). This point is also underlined by Hajkowicz et al. (2016), who stressed that, as work tasks that are routine, repetitive, structured and rules-based are expected to be increasingly automated, modern automation technologies including robotics and artificial intelligence are placing greater emphasis on skills related to creativity, problem-solving, advanced reasoning, complex judgement, social interactions, as well as emotional intelligence as already illustrated throughout this work. As a result, a key objective for education providers should be to ensure that individuals are adequately taught in and equipped with skills that, instead of being in competition with automation technologies, are complementary to them (Hajkowicz et al., 2016). The important role of education will be discussed in more detail shortly. In line with the aforementioned points, the findings obtained by the executive survey conducted by Bughin et al. (2018) suggest that, while the anticipated changes in the skill requirements of future jobs pose a significant challenge to companies, survey respondents of the study conducted by Bughin et al. (2018) reported that, in order to adequately prepare their workers for the changes and challenges ahead, they plan to put high emphasis on developing a workforce of the future that possesses the relevant skills to complement the integration of modern automation technologies into the workplace and thus, allow the company to leverage the full benefits of these technologies (Bughin et al., 2018). With regard to this, respondents of the survey undertaken by Bughin et al. (2018) reported that a mismatch in skills may act as a constraint for companies to fully seize the potential benefits offered by modern automation technologies as the lack of relevant skills of the workers may negatively influence their financial performance or hamper their growth (Bughin et al., 2018). Moreover, skill development will not only present an important endeavor for companies to fully reap the benefits of automation but also for workers, who may experience a stagnation or decline in wages if they won't develop their skills to adequately fulfill the changing skill requirements (Bughin et al., 2018). In this context, further research conducted by Bughin et al. (2018), in which they explored the adoption of automation technology in nine Northern European countries, suggests that, due to the adoption and implementation of automation, the countries investigated are expected to experience a considerable growth in the imbalance of in-demand skills, which may impede the potential productivity increases provided by modern automation technologies (Bughin et al., 2017; Bughin et al., 2018). As a result, the authors argued that wide-scale retraining measures will be necessary in order to effectively manage this potential future skills gap (Bughin et al., 2017; Bughin et al., 2018). Hence, the above-cited challenges regarding the provision of adequate training and reskilling or upskilling measures necessitate appropriate actions by different stakeholders including policy makers, businesses, individuals, as well as education providers (Manyika, Lund, Chui et al., 2017).

However, in spite of the crucial role of training in the face of changing skill requirements, the findings determined by Nedelkoska and Quintini (2018) indicate that plenty of work still needs to be done in terms of training participation by those workers, who are mainly impacted by technology. As Nedelkoska and Quintini (2018) observed, the workers, who seem most negatively affected by automation, constitute this part of workers that generally encounters a considerable low number of training opportunities offered by their employers. Moreover, Pouliakas (2018) found that the risk of automation is especially high among workers with lower levels of skills and linked to jobs, in which offers for training initiatives for the respective workers seem nonexistent. This latter finding, in turn, intensifies the vulnerability of the workers most at risk of being displaced by technology (Pouliakas, 2018). Consistent with this, the findings established by the World Economic Forum (WEF, 2018) suggest that, as a means to enhance their company's strategic capacity, the majority of employers are planning to focus their reskilling and upskilling initiatives on those employees, who are occupying high value job roles (WEF, 2018). In addition, around 41% of employers intend to concentrate their reskilling and training measures on high-performing employees, while only around 33% of employers would give priority to those employees, who are at a much higher risk of being displaced by automation technology (WEF, 2018). Thus, workers that would most require reskilling and upskilling are also the ones who are most unlikely to be offered such training measures (WEF, 2018). Consistent with this, Zobrist and Brandes (2017) reported that, in fact, those workers, who already possess a relatively low level of training, are those that, at the same time, seem least likely to undergo additional or more training. Conversely, workers with the highest levels of qualification are also most likely to undergo further training, even though workers featuring high levels of education and skills generally face a substantially lower risk to be displaced by automation (Zobrist & Brandes, 2017).

These findings provided above are worrying considering that building an inclusive culture of lifelong learning constitutes an essential measure for assisting affected workers in managing the upcoming changes and challenges brought about by job automation as will be discussed in more detail shortly (WEF, 2018). Consequently, the findings discussed above highlight the need for a more inclusive and proactive approach to issues including retraining and upskilling in order to promote the availability of relevant future skills and to prevent or manage imminent skills shortages more effectively (WEF, 2018). In addition, such a more comprehensive and developed approach to issues concerning skills and training is essential in order to allow an increased share of workers to benefit from the potential opportunities and beneficial effects of sophisticated automation technologies and to enable the workers to work with these technologies in a much more complementary manner, which, in turn, empowers them to work more productively due to, for example, skills augmentation (WEF, 2018). As stressed by Shook and Knickrehm (2018), in order to be able to sufficiently match workers to novel and redesigned jobs, businesses need to establish new and innovative training measures and programs. In view of this, new programs that develop and enhance the skills of workers should be rapid, flexible, tailored, and large-scale in order to fully leverage the collaborative value that results from humans and machines working together (Shook & Knickrehm, 2018). At the same time, the necessity to establish and develop a workforce equipped with the relevant and required skills constitutes a possibility for businesses to establish themselves as learning organizations as well as to yield support and assistance from various stakeholders for their training and skills provisions (Harris et al., 2018; WEF, 2018). Further, in view of the challenges presented above, Nedelkoska and Quintini (2018) highlighted the crucial role of adult learning as a means for the re-training and up-skilling of those workers, whose jobs are being impacted by technology, and thereby assisting workers to shift to new work opportunities (Nedelkoska & Quintini, 2018). In line with this, Vazquez et al. (2019) reported that innovative educational online solutions, such as massive open online courses (MOOCs) may present a fruitful means to support adult learning as they "could overcome the lack of formal training opportunities and be used as a lifelong learning tool to reskill and upskill individuals who would gain occupational or even task-specific skills in a flexible and personalized way" (Vazquez et al., 2019, p. 50). In view of this, LinkedIn Talent Solutions (2019) argued that online learning platforms including LinkedInLearning enable and empower individuals to develop their skills in an easy as well as flexible manner.

Moreover, as already argued earlier in this thesis, job automation is expected to considerably alter the mix of work tasks that are performed by humans as certain tasks will be carried out by automation technology, which, in turn, is expected to entail significant changes in the skill requirements of future jobs (Manyika, Lund, Chui et al., 2017). In view of this, Manyika, Lund, Chui et al. (2017) emphasized that this changing nature regarding work tasks and associated skill demand has essential implications for the requirements and objectives of training measures. In this regard, the researchers pointed out that, for instance, as certain work tasks demanding basic levels of performance in specific skills will potentially be automated, training measures should increasingly focus on those skills required for tasks that are much more difficult to automate, such as social and emotional skills (Manyika, Lund, Chui et al., 2017). In addition, as, according to Manyika, Lund, Chui et al. (2017), workers will increasingly be valued for possessing high levels of interpersonal skills and advanced reasoning, and because those skills are frequently promoted through guided experience, workers may need to be more often coached in apprentice-like environments (Manyika, Lund, Chui et al., 2017). Further, the authors argued that, while the workforce of the future is required to apply to a higher degree expertise and judgement, among other skills, as already argued earlier in this work, training initiatives should put more emphasis on developing fluency with and understanding of information (Manyika, Lund, Chui et al., 2017). In line with the arguments put forward by

Manyika, Lund, Chui et al. (2017), Muro et al. (2019) emphasized the importance of promoting uniquely human skills. In this regard, the researchers stressed that, within the context of this new wave of automation that is powered by sophisticated automation technologies, an increased emphasis should be placed on fostering and developing inherently human skills or so-called soft skills that sophisticated machines and automation technology are, to date, not capable of emulating adequately (Muro et al., 2019). In this sense, Muro et al. (2019) argued that, as automation will effectuate changes in the task structure and content of jobs by, for example substituting for certain tasks while creating new ones, as thoroughly illustrated in the previous chapters, workers will be required to continually reskill, readjust, as well as reorient themselves. This, in turn, necessitates, according to the authors, that training measures should integrate the development and promotion of skills relating to adaptability and constant learning (Muro et al., 2019). In addition, Muro et al. (2019) underlined that, while skills related to human interaction are among the most valuable skills for human workers due to the fact that modern automation technology is, so far, not adequately capable of mirroring these skills, training measures should place special emphasis on developing and fostering interpersonal skills along with emotional intelligence.

In addition, with regard to the importance of training and skill development discussed above, Bughin et al. (2018) noted that there are various measures companies may apply or establish in order to develop a workforce that is fully prepared and equipped for the future world of work. In this regard, the authors stressed that retraining actions will be of crucial importance (Bughin et al., 2018). In view of this, Bughin et al. (2018) pointed out that this retraining initiative may encompass three different action measures. The first action involves the advancement and development of the skills capacity of their employees through the means of teaching them entirely new skills or skills that differ in quality (Bughin et al., 2018). A second measure may focus on advancing the already established skills of workers towards higher levels or increasing the existing skill sets to enable the workers to effectively manage technological change (Bughin et al., 2018). Lastly, a third effort may entail employing entry-level workers with the objective to provide them with training opportunities that allow them to acquire the necessary skills (Bughin et al., 2018). With regard to these proposed action measures, Bughin et al. (2018) pointed out that these are frequently referred to reskilling and upskilling. In this context, the researchers also mentioned that companies have different alternatives to meet their reskilling and upskilling objectives, such as offering training initiatives based on in-house resources and

programs or to establish partnerships with educational systems in order to offer workers external learning options (Bughin et al., 2018).
Moreover, as proposed by Zobrist and Brandes (2017), training should be job-specific so that it becomes evident to the workers which kind of training is beneficial for them and why. This, in turn, will result in an increase of the significance of training measures as well as worker motivation. In addition, organizations should also motivate workers to take part in continuing training, for example, through offering financial incentives or through proposing the division of costs (Zobrist & Brandes, 2017). Consistent with this, Manyika et al. (2017) argued that it is essential to provide supportive measures towards affected workers in the form of, for example, retraining initiatives (Manyika et al., 2017).

Building on these arguments given above, Arnold et al. (2018) emphasized that mere organizational measures regarding training initiatives are not sufficient to address the potential upsurge in inequality due to job automation as discussed earlier. In fact, the authors argued that governmental measures are crucial to assist specific groups of workers in enhancing their skill and qualification levels in order for them to be able to meet the changing job requirements (Arnold et al., 2018). Further, the introduction of such programs should not be hold up until the point where workers have already been made redundant by technology. Rather, the affected workers should be given the possibility to upskill themselves while still occupying their jobs as this will ensure the workers' stability in employment (Arnold et al., 2018). In relation to this, the Z_punkt The Foresight Company (2014) remarked that policy makers should support individuals by, for example, providing information and advice about training as well as assist them by granting financial support in order to promote workers' investment in skills. In this context, Manyika, Lund, Chui et al. (2017) argued that governments may have a certain responsibility in modernizing data collection on the labor market. In this regard, it may be valuable for governments to complement surveys that yield certain economic data with real-time data on the provision of automation technologies or demand for skills, among other things (Manyika, Lund, Chui et al., 2017). This may be realized by fostering collaborations between government statistics agencies and online sources of data, such as job boards or professional platforms like LinkedIn in order to acquire a more comprehensive and precise depiction of, for instance, jobs and skills (Manyika, Lund, Chui et al., 2017).

In relation to this, Bughin et al. (2018) and the World Economic Forum (2018) pointed out that, while businesses themselves have an important role to play in assisting their workers with the challenges faced and in making sure to develop sufficient organizational capacity to effectively manage the shift towards the workforce of the future, they will also increasingly have to seek out partnerships with other stakeholders in order to successfully manage the wide-scale upskilling and retraining challenges they are confronted with (Bughin et al., 2018; WEF, 2018). In this regard, valuable partnership possibilities encompass developing collaborations with education providers to redesign school and college curricula, a point that will be further discussed later in this chapter, as well as with labor unions to promote cross-industry talent mobility (Bughin et al., 2018; WEF, 2018). Besides, building up partnerships with governments may also constitute a beneficial undertaking for developing incentives for lifelong learning, securing shared standards for retraining, as well as for reinforcing protection measures for workers facing transitions (Bughin et al., 2018; WEF, 2018). Overall, the points mentioned above underline the significance and importance of the need for corporations to develop partnerships with other stakeholders in order to effectively manage the reskilling and upskilling challenges and ventures (WEF, 2018).

In relation to the aforementioned points, Bughin et al. (2018) emphasized that, while companies themselves have a certain capacity to offer measures and take efforts aimed at developing a future workforce with the necessary skills to adequately meet the expected changing skill requirements of jobs, other stakeholders also need to play their part in realizing this positive vision of a future workforce equipped with the right skills to thrive in increasingly automated work environments (Bughin et al., 2018). With regard to this, the authors pointed out that, in addition to the central role of educational institutions to assist in developing the skills that will be increasingly required in the future as already thoroughly discussed earlier, both industry associations and labor unions also hold a considerable responsibility in preventing or managing skill shortages as well as assisting in retraining measures in this automation age (Bughin et al., 2018). In Germany, for example, industry associations commonly engage in partnerships with the labor agency in regional labor markets in order to determine specific labor needs of a company (Bughin et al., 2018). In this regard, valuable networks between industry associations, educational institutions, along with the labor agency may provide prospective workers with information concerning labor market dynamics and education opportunities (Bughin et al., 2018). In addition, industry associations may also establish and enlarge specific work-study measures including apprenticeships or on-the-job training as useful means to promote the acquisition and advancement of necessary skills (Bughin et al., 2018). Further, Bughin et al. (2018) remarked that labor unions can also participate in training initiatives. The authors mentioned that in the United Kingdom, for instance, the so-called Union Learning Fund seeks to engage low-skill workers to take part in appropriate training measures (Bughin et al., 2018). Consistent with the aforementioned points, the WEF (2020) emphasized that a multi-stakeholder collaboration may be essential in effectively and successfully managing the changes and challenges discussed earlier in terms of the anticipated future skill trends in the context of automation. More specifically, while employers should proactively assist and support their workforce through adequate measures, governments need to provide adequate funds for reskilling and education programs (WEF, 2020). In addition, labor unions also have an important role to play in providing assistance and protection for workers (WEF, 2020).

In addition to the points outlined above, individuals themselves have a certain responsibility in acquiring and developing the relevant skills required to succeed in the future world of work (Manyika, Lund, Chui et al., 2017; Vazquez et al., 2019). In relation to this, Vazquez et al. (2019) pointed out that it also seems to be essential for individuals to actively invest in skills that are likely to increase in demand in the future, and thus, will be increasingly required in many job roles (Vazquez et al., 2019). In addition, in times where almost every job will undergo changes to some extent, it will be essential for human workers to foster and develop agility, resilience, and flexibility (Manyika et al., 2017). In this regard, fostering the development of skills, such as flexibility, resilience, and creativity, will assist workers in adjusting more easily to an increasingly dynamic work environment (Vazquez et al., 2019). Thus, fostering and investing in those skills will be essential in order for workers to succeed in the changing work environments (Vazquez et al., 2019). In relation to the points cited above, Manyika, Lund, Chui et al. (2017) also emphasized that, as automation technology is expected to increasingly perform certain types of work tasks, individuals themselves will need to place greater emphasis on acquiring and fostering the skills, for which humans have a comparative advantage, such as communication, social and emotional skills, as well as creativity. While acknowledging that both policy makers and businesses possess a certain responsibility in, for example, providing information on the particular types of skills and jobs that are becoming increasingly relevant, the researchers stressed that, eventually, it will be the responsibility of individuals to, for example, understand trends in skill demands and finding ways to effectively signal the acquisition of those skills to potential employers (Manyika, Lund, Chui et al., 2017).

4.2.2 *Lifelong Learning*

As already argued above, providing training opportunities for workers for the purpose of upskilling and reskilling constitutes an essential aspect in the context of changing skill requirements as a result of increasingly automated work environments (see e. g. Bughin et al., 2018; Manyika, Lund, Chui et al., 2017; Shook & Knickrehm, 2018; WEF, 2018; Zobrist & Brandes, 2017). In view of this, as argued by Zobrist and Brandes (2017), both initial and continuing training provisions are essential for developing critical future-proof skills and competencies. In this regard, the authors maintained that continuing training is particularly important for those workers whose jobs are experiencing significant changes due to job automation, as well as for those workers whose jobs dissipated due to automation and, thus, need to find other employment options (Zobrist & Brandes, 2017). In relation to this, Arnold et al. (2018) argued that continuous training is essential in order for workers to meet the changing skill requirements of many jobs. In line with this, the Z_punkt The Foresight Company (2014) emphasized in their report that technological progress and growth necessitates a continuous adaptation of skills in order to stay relevant and successful in the labor market. Similarly, the Foundation for Young Australians (FYA) argued in their report about the future of work and skills that, as work will be undergoing continuous changes throughout the years to come, workers will have to spend more of their worktime on learning (FYA, 2017). More specifically, the FYA (2017) estimated that workers of the future will devote one-third of their working hours to learning on the job, which translates into a 30 percent growth compared to the current hours spent on learning. As noted by the FYA (2017), the implementation of modern automation technologies into our workplaces will not only demand greater emphasis on workers' thinking and interpersonal skills, but also necessitates the continuous learning and relearning of the relevant skills required to succeed in the ever-changing world of work (FYA, 2017). Thus, it is expected that continuous learning will become an essential element of people's working lives (FYA, 2017). In addition, Jones (2020) argued that it is not desirable to build different sets of static skills but, rather, it is more critical to develop workers, who can use their skills and capabilities across various contexts and who are continuous learners.

It is within this context, according to Zobrist and Brandes (2017), that lifelong learning is fundamental. This is also underlined by Manyika, Lund, Chui et al. (2017), who emphasized that, in the face of the new wave of automation, lifelong learning will become ever-more important. This point is also strengthened by the Foundation for Young Australians (FYA), who argued, based on their findings obtained by their research study, that workers of the future will not only be required to display high levels of skills related to critical thinking, problem-solving, communication, as well as interaction with others, but also need to be willing to engage in lifelong learning in order to succeed in workplaces of the future (FYA, 2017). Further, as the relevant skills required to succeed in the future world of work are changing at a fast pace and are becoming increasingly complex, while, at the same time, their natural lifespan declines, placing increased emphasis on lifelong learning is becoming fundamental (D2L Corporation, 2018). In other words, "a lifelong approach to learning is quickly becoming the rule rather than the exception" (D2L Corporation, 2018, p. 13). As noted by Vazquez et al. (2019), lifelong learning involves learning in various contexts and throughout life. Hence, according to Zobrist and Brandes (2017), it is not sufficient for workers to merely obtain those skills and competencies that will stay or become increasingly relevant in the future, as set out earlier, but it is even more important for them to undergo continuing training as this will ensure that the respective workers stay relevant, are capable to swiftly manage appropriate responses to possible changes in their work environment resulting from job automation, and are able to display the required flexibility needed in such a fast-paced environment that is the labor market (Zobrist & Brandes, 2017).

Further, the authors emphasized that the process of lifelong learning presents a personal responsibility for each of us individuals, rather than a sole responsibility resumed by the state or organizations (Zobrist & Brandes, 2017). This is also underlined by the Z_punkt The Foresight company (2014) by noting that, as the work environment is becoming increasingly flexible, workers have a greater individual responsibility to develop their skills. In this regard, individuals may negotiate specific training opportunities for skills development as a component of their work contracts and are required to make use of novel and innovative approaches to learning including training initiatives supported or realized through technology (Z_punkt The Foresight Company, 2014). In this context, individuals should put their focus on skills and competencies that likely will be of high demand in the future, such as adaptability, or advanced cognitive skills (Muro et al., 2019; Manyika, Lund, Chui et al., 2017; Z_punkt The Foresight Company, 2014). In relation to this, the FYA (2017) emphasized that, while stressing that an individual's journey of lifelong learning should already start early in their formal education and proceed throughout their working lives, it is of vital importance for individuals to acknowledge and realize that, in order to succeed throughout their working lives, they need to become continuous and active learners as new automation technologies will continue to change what we do in our jobs (FYA, 2017).

Nevertheless, the state, and, in particular, organizations are able to assist in this process by means of various measures (Zobrist & Brandes, 2017). In this regard, the World Economic Forum (2018) pointed out that, while workers hold without doubt a certain degree of personal responsibility to ensure and establish lifelong learning and career development, they will also need to receive support from governments and employers in order to realize smooth and effective work transitions as well as to obtain adequate opportunities for retraining and upskilling (McCauley, 2018; WEF, 2018). Similarly, while discussing the policy implications of increasingly automated workplaces, Oschinski and Wyonch (2017) emphasized the important role of education providers including colleges and technical schools to offer workers regular learning opportunities throughout the employment lifecycle as the need for workers to continuously adapt to changing situations and circumstances increases. According to the authors, a workforce that is provided with regular opportunities to develop and broaden their skills through continuous education and lifelong learning will display increased productivity and higher job satisfaction levels (Oschinski & Wyonch, 2017). Overall, as stressed by Ceemet (2018), a change in mindsets must take place with regard to the concept of lifelong learning in the sense that lifelong learning should be perceived as being something positive as well as something that is worth devoting resources to, such as time and energy. All in all, it needs to be communicated that continuous training and lifelong learning constitute a win-win situation for both employers and employees (Ceemet, 2018).

With regard to the aforementioned points, it may be essential, according to Zobrist and Brandes (2017), that organizations ingrain the acknowledgement of the significance of continuing training within their organizational culture (Zobrist & Brandes, 2017). Consistent with this, Servoz (2019) emphasized that organizations need to foster a culture of lifelong learning in order to effectively face the challenges brought about by job automation. In line with this, the findings obtained through the survey with approximately 3000 C-level executives from companies across the US and Europe conducted by Bughin et al. (2018) suggest that an essential element for the future success of companies given the new age of automation constitutes a shift in their mindset in the sense that it will be crucial for them to offer their workforces continuous learning opportunities along with establishing a culture of lifelong learning within their organizations (Bughin et al., 2018). In this regard, a substantial share of survey respondents reported that it will be essential for workers to not only advance and develop their skills, but to continue to learn and adjust during the course of their working lives (Bughin et al., 2018). Overall, building a culture of lifelong learning was deemed by survey respondents as the most important change necessary to effectively create the workforce of the future (Bughin et al., 2018). Consistent with this, Sigelman et al. (2019) argued that, while highlighting the importance of lifelong learning within the context of the increasing proliferation and pervasiveness of hybrid jobs requiring hybrid skills as already mentioned earlier, employers need to ensure that continuous, lifelong learning becomes an integral aspect of the work environment as “this enables us to become more “hybrid” in our own special way” (Sigelman et al., 2019, p. 5). In relation to the aforementioned points, the D2L Corporation (2019) emphasized that “learning does not stop once you have obtained your cap and gown” (D2L Corporation, 2019, p. 10). With regard to the central role of educational institutions in equipping individuals with the relevant skill sets needed in an increasingly automated world of work, the authors noted that credentialing programs such as micro-credentialing and competency-based education (CBE) programs can promote the redesign of education in order to nurture and develop a culture of lifelong learning (D2L Corporation, 2019). In terms of CBE programs, the authors remarked that these programs present an effective technique to enable individuals holding a certain base layer of knowledge to swiftly advance through a certain program where they hold relevant skills, while focusing more of their time on the learning and development of those kind of skills they are not well equipped with yet (D2L Corporation, 2019). Further, Ovanessoff et al. (2018) argued that, due to the increasing importance for workers to hold a diverse skill set in order to thrive in the new world of work highly driven by intelligent automation technologies, which, in turn, necessitates that increased emphasis should be placed on widening the skill variety within each individual worker, lifelong learning approaches need to include a wide range of distinct skills. In addition, the authors argued that lifelong learning provisions should be available and accessible to all workers in order to mitigate or eliminate skill gaps effectively (Ovanessoff et al., 2018). As already argued earlier and underlined by Ovanessoff et al. (2018), low-skilled job roles are especially susceptible to automation, and workers performing these jobs are in greater need of skill development opportunities. Hence, different stakeholders including governments and businesses must strive for an inclusive approach to lifelong learning in order to prevent the intensification of economic and social inequalities (Ovanessoff et al., 2018).

4.2.3 Education

In view of the findings presented earlier in this thesis, education plays a central role in managing the anticipated changes in skill requirements (Manyika, Lund, Chui et al., 2017; Servoz, 2019). With regard to this, Riad (2017) emphasized that, given increasingly changing workplaces as a result of ongoing technological progress in terms of automation, education systems must foresee and equip workers with the skills required to succeed in the future world of work. According to Riad (2017), this presents an essential condition in order for ensuring effective collaboration between humans and machines that seizes the power and potential of technology, while, at the same time, securing beneficial outcomes for both individuals and societies. Consistent with the aforementioned arguments, Hajkowicz et al. (2016) emphasized that, besides offering appropriate training measures as already discussed earlier, providing sufficient access to high quality education constitutes one of the most effective means to ensure that the workforce of the future will be adequately prepared and equipped with the necessary skills to thrive in the workplaces of the future.

However, as argued by Servoz (2019), the manner in which learning is currently organized within educational systems fails to acknowledge the changes and dynamics instigated by this new wave of automation and its associated technologies. For example, Servoz (2019) pointed out that learning is currently organized in a way that focuses on preparing individuals for specific jobs as opposed to ensuring the acquisition and development of transversal skills (Servoz, 2019). As already mentioned earlier, transversal or transferable skills can be described as skills "that can be applied in varied contexts" (Deloitte, 2017, p. 4), and, thus, constitute skills that are not specifically associated with one particular job, work task, or knowledge area, but present skills that may be applied in a wide range of situations and work settings (Sudhakar, 2018).

Moreover, even though current research points to the importance of acquiring and developing certain kind of skills that will likely become increasingly relevant in the future, and therefore will be required as part of many future jobs, many educational institutions, such as schools and universities, do not sufficiently integrate the teaching and development of those skills in their curricula (Vazquez et al., 2019). Further, it is reported that in the majority of EU countries, the teaching and development of non-cognitive skills including creativity, innovation, and entrepreneurship is not adequately reflected in vocational education and training systems (Cedefop, 2015; Vazquez et al., 2019). Moreover, as the findings presented in the realm of this thesis have shown, in the coming years, workers are expected to increasingly perform work tasks demanding, among others, social and emotional skills as well as skills related to creativity and problem-solving (see e. g. Bughin et al., 2018; Cedefop, 2018; Manyika, Lund, Chui et al. 2017). However, as pointed out by Manyika, Lund, Chui et al. (2017), these kinds of skills are often not integrated in the formal curriculum of education providers such as schools. Furthermore, the proportion of workers not occupying a job in the domain in which they were trained and educated is increasing (Vazquez et al., 2019). This phenomenon is commonly referred to as a horizontal mismatch (Vazquez et al., 2019). Concerning this issue, horizontal mismatches may point to the fact that individuals are not being appropriately trained and educated in skills that are increasingly demanded in the labor market, which may be, to some extent, the result of education systems not being sufficiently receptive to changing and dynamic skill needs (OECD, 2019a; Vazquez et al., 2019). Overall, the points mentioned above suggest that, at present, education systems are not possessing the adequate capacities in order to address the changing labor market needs and successfully prepare individuals for the anticipated changes and challenges associated with the skill requirements of jobs (OECD, 2019a; Manyika, Lund, Chui et al., 2017; Servoz, 2019; Vazquez et al., 2019).

Thus, as argued by Manyika, Lund, Chui et al. (2017), the issues described above necessitate the adjustments and adaptations of education systems and curricula in a way, which adequately reflects the anticipated challenges in terms of future skill demand in order to equip individuals with the necessary skills that are becoming increasingly relevant in dynamic labor markets. Thus, education systems will have to adapt to the dynamic and changing requirements of the labor market to secure the provision of learning of skills that are becoming increasingly critical in the future (Manyika, Lund, Chui et al., 2017). Hence, unless they put more emphasis on adjusting and responding adequately to changing labor market needs, education providers risk promoting an increasingly growing division between education and employment (Manyika, Lund, Chui et al., 2017). In line with this, Pouliakas (2018) argued that it is essential to modernize and modify education systems in a way for them to put greater emphasis on competences and skills that prove to be more difficult even for sophisticated automation technology to appropriate or display, such as communication, collaboration, creativity, and critical thinking (Pouliakas, 2018). In relation to this, it will be essential for governments to acknowledge the impact of intelligent automation on the labor market and employment by modernizing and advancing education policies designed to rapidly promote the level of education and skills of all individuals, especially in reference to skills related to the field of science, technology, engineering, and mathematics (STEM), as well as non-cognitive soft skills that empower individuals to utilize their inherently human capabilities (Hawksworth et al., 2018; McCauley, 2018; WEF, 2018). In reference to the skills related to STEM, Manyika, Lund, Chui et al. (2017) argued that, as demand is expected to grow for workers to develop and implement technology or understand and act on the data analytics that technology is able to generate, the development of STEM skills will be a critical endeavor. In this respect, relevant aspects that need to be addressed encompass school curricula, teacher training, as well as a redesign of vocational training that reflects the changes and challenges of the new wave of automation in the context of the fourth industrial revolution (Hawksworth et al., 2018; McCauley, 2018; WEF, 2018). Moreover, as efforts are taken to transform and develop education and skills policies and action measures in order to promote the employability of individuals, this, in turn, will necessitate specific activities that stimulate the demand side (Hawksworth et al., 2018; WEF, 2018). In other words, in order for further investments in education and skills to become effective, the availability of sufficient jobs for individuals to perform needs to be ensured (Hawksworth et al., 2018). Concerning this matter, governments can support new job creation, for example, through additional public and private investments (Hawksworth et al., 2018; WEF, 2018). All in all, while both education providers and employers have a key responsibility to ensure and promote the implementation of new learning systems that will adequately equip students and workers with the necessary skills to succeed in increasingly automated workplaces (D2L Corporation, 2019), both depend on the government sector "to be the enabler of change" (D2L Corporation, 2019, p. 13). In view of this, government policy needs to support educational institutions with appropriate investments and flexibility to develop effective programs that are based on timely workforce needs, while also providing organizations and education providers with incentives to offer adequate responses to changing workforce needs (D2L Corporation, 2019).

Moreover, organizations may cooperate with education providers as a means to put increased emphasis and attention towards the development of capabilities and skills that will likely increase in demand in the future as analyzed earlier in this work, such as creativity, comprehending and sensing human emotions (Manyika et al., 2017). Strengthening this argument, the Z_punkt The Foresight Company (2014) also argued in their report that collaborating with education and training providers presents an important measure in order to yield access to relevant skills. In accordance with this, Jones (2020) also emphasized that it is important for organizations to actively seek out and create new alliances and relationships with education providers. Consistent with the arguments provided above, Bughin et al. (2018) also emphasized that collaborations between companies and educational institutions can constitute valuable means to modernize curricula as well as to develop the necessary skills. In this regard, on the basis that several voices including specific experts underlined the necessity for universities, colleges, and other educational providers to engage more actively in seeking to adequately meet the changing labor market needs, Winde et al. (2019), for example, proposed for universities to become more proficient in determining ongoing labor market trends and to respond appropriately by, for instance, raising the availability of courses concerned with data science and other technology-related courses (Bughin et al., 2018; Winde et al., 2019). In relation to this, education and training providers themselves have a certain responsibility in that they should sufficiently support organizations in realizing their skills objectives by, for example, ascertaining that measures and provisions reflect appropriate and forward-looking responses to the challenges faced by individuals and organizations (Z_punkt The Foresight Company, 2014). Thus, promoting relationships between organizations and education and training providers seems to be important in order to develop the skills required to function in a fast-pacing work environment (Z_punkt The Foresight Company, 2014). In this context, Bughin et al. (2018) pointed out that technology can assist in establishing a greater connectivity between education providers and companies. In this regard, the researchers remarked that technological tools that can be utilized to bridge the gap between educations systems and businesses have a number of benefits (Bughin et al., 2018). For instance, while virtual and remote programs are more cost efficient than traditional in-person classes, other tools including massive open online courses (MOOCs) and code schools may considerably decrease the time required to obtain the skills that usually demanded the participation in traditional, degree-based programs (Bughin et al., 2018). In addition, part-time educational courses or nondegree certificate programs may enable wider access compared to full-time courses, in particular with regards to adult education (Bughin et al., 2018).

Moreover, as already illustrated in detail earlier, new sophisticated automation technologies are expected to increase the demand for so-called human-centric occupations as those jobs demand skills that currently prove to be very difficult to automate including skills related to empathy and complex communication (see e. g. AIG, 2018; Bakhshi et al., 2017; Bughin et al., 2018;

Cedefop, 2018; Dellot & Wallace-Stephens, 2017; Manyika, Lund, Chui et al., 2017; Servoz, 2019). In view of this, Dellot and Wallace-Stephens (2017) stressed that, due to increasingly automated work environments, the development of new and modern schooling methods that aim to promote soft skills that, for now, can't be adequately replicated by even advanced automation technology, will need to be made a high priority. With regard to this, the authors advocated that, in order to effectively prepare young individuals to meet the required skill demands of future jobs, both the government and education providers should promote the design and establishment of new and innovative schooling models that foster relevant skills associated with problem-solving, critical thinking, as well as entrepreneurial mindsets (Dellot & Wallace-Stephens, 2017). The discussion and analysis in the present chapter and preceding chapters clearly illustrate that, within the context of increasingly automated workplaces of the future, entrepreneurial thinking skills will not only be valuable skills for business owners and business leaders to possess but will also be of high value for the general future workforce (AIG, 2018; Foundation for Young Australians, 2016; Oschinski & Wyonch, 2017). Thus, according to Oschinski and Wyonch (2017), the provision of adequate learning opportunities in order for individuals to acquire and develop such entrepreneurial skills will be essential and will require a joint effort and collaboration by the public sector, the private sector, and educational institutions.

4.2.4 Summary

As already mentioned earlier, the changes in jobs and skill requirements resulting from job automation necessitate appropriate responses from a variety of stakeholder including individuals, organizations, as well as education providers and policy makers in order to effectively manage and prepare for the future world of work and its associated changes and challenges (see e. g. Arnold et al., 2018; McKay et al., 2019; Patscha et al., 2017; Riad, 2017; Servoz, 2019; Z-punkt The Foresight Company, 2014). In this regard, the foregoing discussion sought to address these issues by highlighting some key measures and actions that should be taken into account when aiming to face the anticipated changes in skill requirements of jobs effectuated by the increasing adoption and implementation of modern automation technologies in work environments. In view of this, a successful undertaking with regard to adequately preparing for and managing future skill shifts requires, but is not limited to, education systems that teach the skills needed to thrive in future labor markets, businesses that sufficiently assist their workers through offering adequate retraining and upskilling opportunities, individuals, who actively engage in lifelong learning, as well as governments that establish the necessary conditions to realize these action measures and efforts (see e. g. Bughin et al., 2018; Manyika, Lund, Chui et al., 2017; Ovanessoff et al., 2018; Riad, 2017; WEF, 2016; WEF, 2018; WEF, 2020; Zobrist & Brandes, 2017). As stressed by Riad (2017), through sufficient implementation and realization of the efforts needed to effectively face and manage the anticipated changes in skill requirements of future jobs due to ongoing technological progress with regard to automation technology, human workers will be able to work effectively with machines, rather than against them, thereby unlocking all of the potential offered by technology (Riad, 2017). Overall, as stressed by Capita (2019), being able to provide an adequate response to the challenges resulting from automation in the context of future skills demands multi-stakeholder action in order to ascertain that every individual can succeed and thrive in an increasingly automated world of work (Capita, 2019).

All in all, although the proposed measures and actions may present effective and critical efforts in order to respond appropriately to the dynamics, challenges and changes brought about by job automation with regard to the skill requirements of jobs across advanced economies, it is important to emphasize that these provisions should not be viewed as conclusive and definite solutions or responses to the challenges discussed earlier, but rather present a starting point to incite and encourage further consideration, reflection, and discussion about these highly prevalent themes (see e.g. Z_punkt The Foresight Company, 2014).

5 Conclusion

"The world of work is changing. It always has. It always will" (Delisle, 2019, p. 68). Modern and sophisticated automation technologies that include, but are not limited to, robotics, artificial intelligence, and machine learning, are causing fundamental changes in the nature of work (Engler et al., 2018). In view of this, recent and ongoing technological advances enable modern automation technologies to potentially perform an increasing range of jobs and work tasks, thereby changing the role of humans in the context of the work environment in fundamental ways (Delisle, 2019; OECD, 2019b). As already argued above, while some jobs may be entirely displaced by technology, it is anticipated that a vast number of jobs are substantially altered and reshaped and completely new jobs may emerge (Manyika et al., 2017; Nedelkoska & Quintini, 2018; Vazquez et al., 2019). In view of this, even though ongoing technological advances in the context of automation are unlikely to effectuate widescale unemployment across advanced economies within the near future, it is, nevertheless, expected that job automation will constitute a disruptive force to the world of work (see e. g. Patscha et al., 2017; Seet et al., 2018).

As a result, as shown by the synthesis of relevant findings generated from the literature together with the findings and insights obtained by means of the expert interviews conducted in the realm of this thesis, the skill requirements of jobs are expected to undergo certain changes over the next few years. More specifically, the overall findings and insights presented and discussed earlier suggest that, while automation is expected to increasingly take over those tasks or jobs that are largely based on physical and manual skills as well as basic cognitive skills, the emphasis for human workers is put more heavily on those work tasks or jobs that necessitate sophisticated levels of skills that, at least for now, cannot be adequately emulated by even advanced automation technologies. In view of this, while physical and manual skills along with basic cognitive skills are anticipated to decline in demand in the years to come, skills associated with the categories of social and emotional skills, advanced cognitive skills, as well as systems skills are expected to increase in demand within the next few years, thereby changing the skill requirements accordingly. In addition, due to the increasing adoption and implementation of modern automation technologies into the work environment that are considered to take place within the next few years, the overall findings from both the literature as well as the expert interviews also point towards an expected increase in demand for technological and digital skills that, among other purposes as illustrated earlier in this work, enable the workers to work effectively with the respective automation technologies. Moreover, the overall findings also suggest that, in order for workers to strengthen their chances to thrive and succeed in the future world of work that is anticipated to be increasingly characterized and shaped by the adoption and implementation of sophisticated automation technologies, it will be beneficial for workers to be sufficiently proficient in a portfolio of diverse skills pertaining to the distinct skill categories that are expected to increase in demand within the next few years.

Overall, in view of the aforementioned points, it seems reasonable to conclude that, within the next few years, job automation will likely change the skill requirements of jobs in a way that reflects and is correspondent to the trends presented in Table 2. However, as illustrated throughout Chapter 4.1, certain points may require further attention and clarification in order to truly make the best possible predictions that entail a highly informative value for the decision-making of various stakeholders. Nevertheless, it needs to be emphasized once again at this point that forward-looking research projects along with their estimates, predictions, or forecasts inevitably entail a certain degree of uncertainty that should always be accounted for when making decisions based on such predictive forecasts.

Further, while the adoption and implementation of modern automation technologies into the work environment potentially entail various opportunities and may generate beneficial outcomes, it must not be neglected that the resulting changes in the skill requirements of jobs that are anticipated to unfold are expected to also bring with them certain challenges that various stakeholders will need to face and manage appropriately (see e. g. Bughin et al., 2018; Servoz, 2019; WEF, 2018). As a result, the anticipated challenges necessitate various action measures and efforts that need to be established or promoted by different stakeholders, and that may include, but are not limited to, the promotion of a lifelong learning organizational culture, the provision of inclusive activities and programs for reskilling and upskilling ventures, as well as the redesign and modernization of educational programs (see e. g. Bughin et al., 2018; Manyika, Lund, Chui et al., 2017; Ovanessoff et al., 2018; Riad, 2017; WEF, 2016; WEF, 2018; WEF, 2020; Zobrist & Brandes, 2017).

To conclude, while it is acknowledged that the present work is not without limitations as already discussed earlier and entails a certain degree of uncertainty due to its forward-looking manner, it still generated some valuable insights that may be useful for a variety of stakeholders including individuals, businesses, and education providers. Overall, by aiming to provide a comprehensive answer to the central research question that the present thesis focused on, this work sought to contribute to the understanding of the anticipated changes in the skill requirements of jobs as a result of increasingly automated work environments, thereby enriching existing knowledge about this prevalent and important topic.

Bibliography

Acaroglu, L. (2017). *Tools for systems thinkers: The 6 fundamental concepts of systems thinking*. https://medium.com/disruptive-design/tools-for-systems-thinkers-the-6-fundamental-concepts-of-systems-thinking-379cdac3dc6a

Acemoglu, D., & Restrepo, P. (2018). *Artificial intelligence, automation and work* (No. 0898–2937). National Bureau of Economic Research. https://www.nber.org/system/files/working_papers/w24196/w24196.pdf

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, *33*(2), 3–30.

AIG (Australian Industry Group). (2018). *Developing the workforce for a digital future: Addressing critical issues and planning for action*. Australian Industry Group. https://www.voced.edu.au/content/ngv%3A79340

AiGroup. (2018). *Equipping your company with digital capabilities for the future*. Australian Industry Group. https://cdn.aigroup.com.au/Reports/2018/A_company_guide_to_equipping_your_workforce_with_skills_for_the_future.pdf

Allan, K. (2020). *How technology is changing the role of the manager*. https://www.itpro.co.uk/business-strategy/careers-training/355179/how-technology-is-changing-the-role-of-the-manager

Allas, T., Dimson, J., Foote, E., & Jeffery, B. (2019). *The future of work: Rethinking skills to tackle the UK's looming talent shortage*. McKinsey & Company. https://www.mckinsey.com/featured-insights/future-of-work/the-future-of-work-rethinking-skills-to-tackle-the-uks-looming-talent-shortage

Allen, R., Teodoro, N., & Manley, C. (2017). *Future skills and training: A practical resource to* *help identify future skills and training*. Australian Industry and Skills Committee. https://www.aisc.net.au/sites/aisc/files/documents/Future%20Priority%20Skills%20Resource.pdf

AlphaBeta. (2017). *The automation advantage: How Australia can seize a $2 trillion opportunity from automation and create millions of safer, more meaningful and more valuable jobs*. AlphaBeta. https://www.alphabeta.com/wp-content/uploads/2017/08/The-Automation-Advantage.pdf

Anderson, L. W., Krathwohl, D. R., Airasian, P. W., Cruikshank, K. A., Mayer, R. E., Pintrich, P. R., Raths, J., & Wittrock, M. C. (2001). *A taxonomy for learning, teaching, and assessing*. Pearson. https://www.uky.edu/~rsand1/china2018/texts/Anderson-Krathwohl%20-%20A%20taxonomy%20for%20learning%20teaching%20and%20assessing.pdf

Aratani, L. (2020). *Robots on the rise as Americans experience record job losses amid pandemic*. The Guardian. https://www.theguardian.com/technology/2020/nov/27/robots-replacing-jobs-automation-unemployment-us

Arnold, D., Arntz, M., Gregory, T., Steffes, S., & Zierahn, U. (2018). No need for automation angst, but automation policies. In *Work in the digital age* (pp. 75–87).

Arntz, M., Gregory, T., & Zierahn, U. (2016). *The risk of automation for jobs in OECD countries: A comparative analysis* (No. 189; OECD Social, Employment and Migration Working Papers, pp. 1–34). OECD. https://www.oecd-ilibrary.org/docserver/5jlz9h56dvq7-en.pdf?expires=1589261473&id=id&accname=guest&checksum=CA8460F9E5C369DD1296DB2EFB2FBAC1

Atkinson, R. D. (2016). 'It's Going to Kill Us!'And Other Myths About the Future of Artificial Intelligence. *Information Technology & Innovation Foundation*. https://files.eric.ed.gov/fulltext/EJ1121424.pdf

Atkinson, R. D. (2018). Emerging technologies and preparing for the future labor market.

Information Technology & Innovation Foundation, 1–26.

Atkinson, S. P. (n.d.). *The role of the psychomotor domain in higher education*. SIJEN. https://sijen.com/tag/manual-skills/

Autor, D. (2014). Polanyi's paradox and the shape of employment growth. *National Bureau of Economic Research*, *20485*(NBER Working Paper Series), 46.

Autor, D. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, *29*(3), 3–30.

Autor, D. H., & Handel, M. J. (2013). Putting tasks to the test: Human capital, job tasks, and wages. *Journal of Labor Economics*, *31*(2), 59–96.

Autor, D. H., Levy, F., & Murnane, R. J. (2000). Upstairs, downstairs: Computer-skill complementarity and computer-labor substitution on two floors of a large bank. *NBER Working Paper Series*.

Bakhshi, H., Downing, J. M., Osborne, M. A., & Schneider, P. (2017). *The future of skills: Employment in 2030* (p. 121). Pearson. https://futureskills.pearson.com/research/assets/pdfs/technical-report.pdf

Baweja, B., Donovan, P., Haefele, M., Siddiqi, L., & Smiles, S. (2016). *Extreme automation and connectivity: The global, regional, and investment implications of the Fourth Industrial Revolution*. *18*. https://www.ip-watch.org/weblog/wp-content/uploads/2017/09/ubs-vierte-industrielle-revolution-2016-01-21.pdf

Beaumont, L. R. (n.d.). *Emotional Competency*. http://www.emotionalcompetency.com/

Bessen, J., Goos, M., Salomons, A., & van den Berge, W. (2020). *Automation: A Guide for Policymakers*. Brookings. https://www.brookings.edu/wp-content/uploads/2020/01/Bessen-et-al_Full-report.pdf

Bisello, M., Peruffo, E., Fernández-Macías, E., & Rinaldi, R. (2019). *How computerisation is transforming jobs: Evidence from the Eurofound's European Working Conditions Survey*. JRC

Working Papers Series on Labour, Education and Technology. https://ideas.repec.org/p/ipt/laedte/201902.html

Bloom, B. S. (1956). *Taxonomy of educational objectives: The classification of educational goals*. Longmans, Green and Co LTD. https://www.uky.edu/~rsand1/china2018/texts/Bloom%20et%20al%20-Taxonomy%20of%20Educational%20Objectives.pdf

Bloomberg Intelligence. (2017). *A new era: Artificial intelligence is now the biggest tech disrupter*. https://www.bloomberg.com/professional/blog/new-era-artificial-intelligence-now-biggest-tech-disrupter/

Bonin, H., Gregory, T., & Zierahn, U. (2015). *Übertragung der Studie von Frey/Osborne (2013) auf Deutschland*. Zentrum für Europäische Wirtschaftsforschung GmbH. https://www.bmas.de/SharedDocs/Downloads/DE/PDF-Publikationen/Forschungsberichte/fb-455.pdf?__blob=publicationFile&v=1

Bovaird, V., Kundu, S., Moir, J., Sanmugananthan, S., & Turk, D. (2017). Automation is here to stay...but what about your workforce? Preparing your organization for the new worker ecosystem. *Deloitte*, 16.

Bowles, J. (2014). *The computerization of European jobs: Who will win and who will lose from the impact of new technology onto old areas of employment?* https://www.bruegel.org/2014/07/chart-of-the-week-54-of-eu-jobs-at-risk-of-computerisation/

Brooks, J., & King, N. (2014). Doing template analysis: Evaluating an end of life care service. *Sage Research Methods Cases*.

Brooks, J., McCluskey, S., Turley, E., & King, N. (2015). The utility of template analysis in qualitative psychology research. *Qualitative Research in Psychology*, *12*(2), 202–222.

Brown, J., Gosling, T., Sethi, B., Sheppard, B., Stubbings, C., Sviokla, J., Williams, J., & Zarubina, D. (2017). *Workforce of the future: The competing forces shaping 2030*. PwC.

https://www.pwc.com/gx/en/services/people-organisation/workforce-of-the-future/workforce-of-the-future-the-competing-forces-shaping-2030-pwc.pdf

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.

Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. *AAAS*, *358*(6370), 1530–1534.

Brzeski, C., & Burk, I. (2015). Die Roboter kommen. Folgen der Automatisierung für den deutschen Arbeitsmarkt. *INGDiBa*, 7.

Bughin, J., Staun, J., Andersen, J. R., Schultz-Nielsen, M., Aagaard, P., & Enggaard, T. (2017). *Digitally-Enabled Automation and Artificial Intelligence: Shaping the Future of Work in Europe's Digital Front-runners*. McKinsey & Company. https://www.voced.edu.au/content/ngv%3A78849

Bughin, Jacques, Hazan, E., Lund, S., Dahlström, P., Wiesinger, A., & Subramaniam, A. (2018). *Skill shift: Automation and the future of the workforce*. McKinsey & Company. https://www.mckinsey.com/~/media/McKinsey/Industries/Public%20and%20Social%20Sector/Our%20Insights/Skill%20shift%20Automation%20and%20the%20future%20of%20the%20workforce/MGI-Skill-Shift-Automation-and-future-of-the-workforce-May-2018.pdf

Bughin, Jaques, Hazan, E., Allas, T., Hjartar, K., Manyika, J., Sjatil, P. E., & Shigna, I. (2019). *Tech for Good: Smoothing disruption, improving well-being*. McKinsey Global Institute. https://www.mckinsey.com/featured-insights/future-of-work/tech-for-good-using-technology-to-smooth-disruption-and-improve-well-being

Business Council of Australia. (2016). *Being Work Ready: A Guide to What Employers Want*. Business Council of Australia. https://d3n8a8pro7vhmx.cloudfront.net/bca/pages/4101/attachments/original/1527731958/Being_Work_Ready_Guide.pdf?1527731958

Caballar, R. D. (2019). *What is the Uncanny Valley? Creepy robots and the strange phenomenon of the uncanney valley: Definition, history, examples, and how to avoid it*. IEEE Spectrum. https://spectrum.ieee.org/automaton/robotics/humanoids/what-is-the-uncanny-valley

Capita. (2019). *Robot wars or automation alliances?* https://www.capita.com/sites/g/files/nginej146/files/2019-11/capita-future-of-work-report.pdf

Cedefop. (2015). *Skill shortages and gaps in European enterprises: Striking a balance between vocational education and training and the labour market*. Publications Office Luxembourg. https://www.cedefop.europa.eu/files/3071_en.pdf

Cedefop. (2017). People, machines, robots and skills. *European Centre for the Development of Vocational Training*, 4.

Cedefop. (2018). *Insights into skill shortages and skill mismatch: Learning from Cedefop's European skills and jobs survey*. European Centre for the Development of Vocational Training. https://www.cedefop.europa.eu/files/3075_en.pdf

Cedefop. (2019). *The skills employers want!* (p. 4). European Centre for the Development of Vocational Training. https://www.cedefop.europa.eu/files/9137_en.pdf

Ceemet. (2018). *Digitalisation and the world of skills and education* (p. 21). Ceemet. https://www.ceemet.org/sites/default/files/ceemet_digitalisation_and_skills_report_spreads.pdf

Chang, J.-H., & Huynh, P. (2016). *ASEAN in transformation: The future of jobs at risk of automation*. International Labour Organization. https://www.ilo.org/wcmsp5/groups/public/---ed_dialogue/---act_emp/documents/publication/wcms_579554.pdf

Chui, M., Manyika, J., & Miremadi, M. (2016). Where machines could replace humans—And where they can't (yet). *McKinsey Quarterly*, *30*(2), 1–9.

Collings, D., & McMackin, J. (2019). *Enabling the workforce of the future: The role of learning and development*. https://www.skillnetireland.ie/wp-content/uploads/2019/12/trainers-learning-

Skillnet-report-Enabling-The-Workforce-Of-The-Future.pdf

Creswell, J. W., & Poth, C. N. (2016). *Qualitative inquiry and research design: Choosing among five approaches*. Sage publications.

Crowe, A., Dirks, C., & Wenderoth, M. P. (2008). Biology in Bloom: Implementing Bloom's taxonomy to enhance student learning in biology. *Life Sciences Education*, *7*(4), 368–381.

Cunningham, W., & Villaseñor, P. (2014). Employer voices, employer demands, and implications for public skills development policy. *World Bank Group*. https://openknowledge.worldbank.org/handle/10986/27700

Curtarelli, M., Gualtieri, V., Jannati, M. S., & Donlevy, V. (2016). *ICT for work: Digital skills in the workplace*. https://www.voced.edu.au/content/ngv%3A76713

D2L Corporation. (2018). *The future of work and learning in the age of the 4th industrial revolution*. D2L Corporation. https://www.d2l.com/wp-content/uploads/2018/01/The-Future-of-Work-and-Learning-D2L.pdf

D2L Corporation. (2019). *The future of skills in the age of the 4th Industrial Revolution*. D2L Corporation. file:///Users/ameliekraft/Downloads/The-Future-of-Skills-Whitepaper-1.pdf

Daheim, C., & Wintermann, O. (2016). *2050: The Future of Work. Findings of an international Delphi Study of the Millennium Project.* Bertelsmann Stiftung. https://www.bertelsmann-stiftung.de/fileadmin/files/BSt/Publikationen/GrauePublikationen/BST_Delphi_E_03lay.pdf

Dahlin, E. (2019). Are Robots Stealing Our Jobs? *Socius*, *5*, 2378023119846249.

Davenport, T. H., & Kirby, J. (2015). *Beyond Automation*. https://hbr.org/2015/06/beyond-automation

Dawson, R. (2017). *The Commonwealth Bank jobs and skills of the future report*. Commonwealth Bank. https://rossdawson.com/wp-content/uploads/2017/11/Commonwealth-Bank_Jobs-and-Skills-of-the-Future-Report_November-2017.pdf

Delisle, M. (2019). *Skills of the future for a high-performing workforce: Evidence from research*.

Ottawa, ON: Employment and Social Development Canada.

Dellot, B. (2018). *Why automation is more than just a job killer*. https://www.thersa.org/discover/publications-and-articles/rsa-blogs/2018/07/the-four-types-of-automation-substitution-augmentation-generation-and-transference

Dellot, B., & Wallace-Stephens, F. (2017). *The Age of Automation: Artificial intelligence, robotics and the future of low-skilled work*. https://www.thersa.org/globalassets/pdfs/reports/rsa_the-age-of-automation-report.pdf

Deloitte. (2017). *Soft skills for business success*. Deloitte Access Economics DeakinCo. file:///Users/ameliekraft/Downloads/deloitte-au-economics-deakin-soft-skills-business-success-170517.pdf

Denzin, N. K., & Lincoln, Y. S. (2008). *The landscape of qualitative research* (Vol. 1). Sage.

Eikenberg, D. (2018). *Why soft skills are harder than they look*. Forbes. https://www.forbes.com/sites/forbescoachescouncil/2018/07/12/why-soft-skills-are-harder-than-they-look/?sh=70a8c4b6359e

Ellingrud, K., Gupta, R., & Salguero, J. (2020). Building the vital skills for the future of work in operations. *McKinsey & Company*, 8.

Elliott, S. W. (2017). *Computers and the Future of Skill Demand.* OECD. https://www.oecd.org/education/computers-and-the-future-of-skill-demand-9789264284395-en.htm

Ellis, R. K. (2019). *Hybrid jobs need hybrid skills*. https://www.td.org/insights/hybrid-jobs-need-hybrid-skills

Engler, J., Pritzker, P., Alden, E., & Taylor-Kale, L. (2018). *The work ahead: Machines, skills, and US leadership in the twenty-first century*. Council on Foreign Relations.

Ernst, E., Merola, R., & Samaan, D. (2018). *Economics of Artificial Intelligence: Implications for the Future of Work*. International Labor Organization.

https://www.ilo.org/wcmsp5/groups/public/---dgreports/---cabinet/documents/publication/wcms_647306.pdf

Fernández-Macías, E. (2018). *Automation, digitalisation and platforms: Implications for work and employment*. Eurofound. https://www.eurofound.europa.eu/publications/report/2018/automation-digitisation-and-platforms-implications-for-work-and-employment

Foundation for Young Australians. (2016). *The New Basics: Big Data Reveals the Skills Young People Need for the New Work Order*. FYA Melbourne, VIC, Australia. https://www.fya.org.au/wp-content/uploads/2016/04/The-New-Basics_Update_Web.pdf

Frey, C. B., & Osborne, M. A. (2013). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280.

Frontier Economics. (2018). *The impact of artificial intelligence on work: An evidence synthesis on implications for individuals, communities, and societies*. https://royalsociety.org/~/media/policy/projects/ai-and-work/evidence-synthesis-the-impact-of-AI-on-work.PDF

FutureLearn. (2020). 7 skills employers of the future will be looking for. *FutureLearn*. https://www.futurelearn.com/info/blog/careers/7-skills-employers-of-the-future-will-be-looking-for

FYA (Foundation for Young Australians). (2017). *The New Work Smarts: Thriving in the New Work Order*. https://www.fya.org.au/wp-content/uploads/2017/07/FYA_TheNewWorkSmarts_July2017.pdf

GAO. (2019). *Workforce automation: Better data needed to assess and plan for effects of advanced technologies on jobs*. https://www.gao.gov/assets/700/697366.pdf

Gentili, A., Compagnucci, F., Gallegati, M., & Valentini, E. (2020). Are machines stealing our jobs? *Cambridge Journal of Regions, Economy and Society*, *13*(1), 153–173.

Globerman, S. (2019). *Technology, automation and employment: Will this time be different?* Fraser Institute. https://www.fraserinstitute.org/studies/technology-automation-and-employment-will-this-time-be-different

Goos, M., Arntz, M., Zierahn, U., Gregory, T., Gomez, S. C., Vazquez, I. G., & Jonkers, K. (2019). *The Impact of Technological Innovation on the Future of Work* (JRC Technical Report No. 2019/03; JRC Working Papers Series on Labour, Education and Technology). European Commission. https://ec.europa.eu/jrc/sites/jrcsh/files/jrc117212.pdf

Greiff, S., Wüstenberg, S., Goetz, T., Vainikainen, M.-P., Hautamäki, J., & Bornstein, M. H. (2015). A longitudinal study of higher-order thinking skills: Working memory and fluid reasoning in childhood enhance complex problem solving in adolescence. *Frontiers in Psychology*, *6*, 9.

Gumbel, P. (2018, March 23). *How will automation affect jobs, skills, and wages?* https://www.mckinsey.com/featured-insights/future-of-work/how-will-automation-affect-jobs-skills-and-wages

Hajkowicz, S., Reeson, A., Rudd, L., Bratanova, A., Hodgers, L., Mason, C., & Boughen, N. (2016). Tomorrow's digitally enabled workforce: Megatrends and scenarios for jobs and employment in Australia over the coming twenty years. *Australian Policy Online*. https://www.researchgate.net/publication/299953345_Tomorrow's_digitally_enabled_workforce_Megatrends_and_scenarios_for_jobs_and_employment_in_Australia_over_the_coming_twenty_years

Harrell, M. C., & Bradley, M. A. (2009). *Data collection methods: Semi-structured interviews and focus groups*. RAND National Defense Research Institute. https://www.rand.org/pubs/technical_reports/TR718.html

Harris, K., Kimson, A., & Schwedel, A. (2018). *Labor 2030: The collision of demographics, automation and inequality.* Bain & Company. https://www.bain.com/insights/labor-2030-the-collision-of-demographics-automation-and-inequality/

Harter, J. (2020). *Who should lead automation-driven changes?* https://savigent.com/who-should-lead-automation-driven-changes/

Hawksworth, J., Berriman, R., & Goel, S. (2018). *Will robots really steal our jobs? An international analysis of the potential long-term impact of automation*. PwC. https://www.pwc.com/hu/hu/kiadvanyok/assets/pdf/impact_of_automation_on_jobs.pdf

Hennink, M., Hutter, I., & Bailey, A. (2020). *Qualitative research methods*. SAGE Publications Limited.

Hoffman, B. J., Shoss, M. K., & Wegman, L. A. (2020). *The Cambridge Handbook of the Changing Nature of Work*. Cambridge University Press.

ILO. (2018). *Global skill trends, training needs and lifelong learning strategies for the future of work*. International Labour Office. https://www.ilo.org/wcmsp5/groups/public/---dgreports/---inst/documents/publication/wcms_646038.pdf

Ilomäki, L., Kantosalo, A., & Lakkala, M. (2011). What is digital competence? *Linked Portal*. https://core.ac.uk/download/pdf/33734457.pdf

Indeed. (2020). *Cognitive skills: What they are and how to improve them*. https://www.indeed.com/career-advice/career-development/cognitive-skills-how-to-improve-them

Jones, R. (2020). *Work disrupted, education disrupted* [Interview]. https://sloanreview.mit.edu/offers-free-download-future-ready-workforce/

Karsten, J., & West, D. M. (2016). Encryption debate proves technology is not magic. *Brookings*. https://www.brookings.edu/blog/techtank/2016/04/26/encryption-debate-proves-technology-is-not-magic/

Khullar, H. (2020). *Cognitive skills: Definition, examples, and how to improve them*. Shinelearning. https://learning.shine.com/talenteconomy/career-help/cognitive-skills/

Khurana, R. (2018). *Job automation should be celebrated, not feared*. Foundation for Economic

Education. https://fee.org/articles/job-automation-should-be-celebrated-not-feared/

King, N. (2004a). Using interviews in qualitative research. In *Essential guide to qualitative methods in organizational research* (pp. 11–22). Sage.

King, N. (2004b). Using templates in the thematic analysis of text. In *Essential guide to qualitative methods in organizational research* (pp. 256–270). Sage.

King, N., & Brooks, J. M. (2016). *Template analysis for business and management students*. Sage.

King, N., Carroll, C., Newton, P., & Dornan, T. (2002). "You can't cure it so you have to endure it": The experience of adaptation to diabetic renal disease. *Qualitative Health Research*, *12*(3), 329–346.

Kirchherr, J., Klier, J., Lehmann-Brauns, C., & Winde, M. (2018). Future skills: Which skills are lacking in Germany. *Stifterverband*. https://www.stifterverband.org/medien/which-skills-are-lacking-in-germany

Kispeter, E. (2018). *Digital Skills and Inclusion Research Working Group Evidence Brief*. Warwick Institute for Employment Research. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/807831/What_digital_skills_do_adults_need_to_succeed_in_the_workplace_now_and_in_the_next_10_years_.pdf

Kosslyn, S. M. (2019). *Are you developing skills that won't be automated?* https://hbr.org/2019/09/are-you-developing-skills-that-wont-be-automated

Krathwohl, D. R. (2002). A revision of Bloom's taxonomy: An overview. *Theory into Practice*, *41*(4), 212–218.

Lamb, C., Munro, D., & Vu, V. (2018). *Better, Faster, Stronger: Maximizing The Benefits Of Automation For Ontario's Firms And People* (p. 114). Brookfield Institute for Innovation+ Entrepreneurship. https://brookfieldinstitute.ca/better-faster-stronger/

Lennon, C. (2018). *Systems thinking in a nutshell*. https://medium.com/swlh/systems-thinking-in-a-nutshell-c3ebab87f37

Liberto, D. (2019). *Advanced Economies*. Investopedia. https://www.investopedia.com/terms/a/advanced-economies.asp

Linder, N., & Frakes, J. (n.d.). *A new path to understanding systems thinking*. https://thesystemsthinker.com/%EF%BB%BFa-new-path-to-understanding-systems-thinking/

LinkedIn Talent Solutions. (2019). *Future of skills 2019: Anticipating what's next for your business*. LinkedIn Talent Solutions, Place of publication not identified. https://business.linkedin.com/talent-solutions/recruiting-tips/future-of-skills-for-asia-pacific-2019

Lowry, D., Molloy, S., & McGlennon, S. (2008). Future skill needs: Projections and employers' views. *Australian Bulletin of Labour*, *34*(2), 192.

Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P., & Dewhurst, M. (2017). *A future that works: Automation, employment, and productivity* (pp. 1–135). McKinsey & Company. https://www.mckinsey.com/~/media/mckinsey/featured%20insights/Digital%20Disruption/Harnessing%20automation%20for%20a%20future%20that%20works/MGI-A-future-that-works-Full-report.ashx

Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., Ko, R., & Sanghvi, S. (2017). *Jobs lost, jobs gained: Workforce transitions in a time of automation*. McKinsey & Company. https://www.mckinsey.com/featured-insights/future-of-work/jobs-lost-jobs-gained-what-the-future-of-work-will-mean-for-jobs-skills-and-wages

Manyika, J., & Sneader, K. (2018). *AI, automation, and the future of work: Ten things to solve for*. McKinsey Global Institute. https://www.mckinsey.com/featured-insights/future-of-work/ai-automation-and-the-future-of-work-ten-things-to-solve-for

Marion, T. J., Fixson, S. K., & Brown, G. (2020). Four Skills Tomorrow's Innovation Workforce

Will Need. *MIT Sloan Management Review*, *61*(2), 1–7.

McCauley, D. (2018). *The automation readiness index: Who is ready for the coming wave of automation?* The Economist Intelligence Unit Limited. https://www.automationreadiness.eiu.com/static/download/PDF.pdf

McKay, C., Pollack, E., & Fitzpayne, A. (2019). *Automation and a Changing Economy. Part 1: The case for action*. The Aspen Institute Future of Work Initiative. https://www.aspeninstitute.org/wp-content/uploads/2019/04/Automation-and-a-Changing-Economy_The-Case-for-Action_April-2019.pdf

Mentalup. (2020). What are social emotional skills? How can you improve them? *Mentalup*. https://www.mentalup.co/blog/social-and-emotional-skills-in-children

Milano, M. (2019). *The digital skills gap is widening fast. Here's how to bridge it.* https://www.weforum.org/agenda/2019/03/the-digital-skills-gap-is-widening-fast-heres-how-to-bridge-it/

Miller, B., & Atkinson, R. D. (2013). Are robots taking our jobs, or making them? *ITIF, September*, *2*.

Mokyr, J., Vickers, C., & Ziebarth, N. L. (2015). The history of technological anxiety and the future of economic growth: Is this time different? *Journal of Economic Perspectives*, *29*(3), 31–50.

Munkittrick, K. (2011). *Thor pays tribute to Arthur C. Clarke's rule about magic and technology*. Discover. https://www.discovermagazine.com/mind/thor-pays-tribute-to-arthur-c-clarkes-rule-about-magic-and-technology

Muro, M., Maxim, R., & Whiton, J. (2019). *Automation and artificial intelligence: How machines are affecting people and places*. Brookings. https://media.africaportal.org/documents/Automation_and_Artificial_intelligence_WAB66GR.pdf

National Mentoring Resource Center. (n.d.). *Social-Emotional skills*.

https://nationalmentoringresourcecenter.org/index.php/toolkit/item/247-social-emotional-skills.html

Nedelkoska, L., & Quintini, G. (2018). *Automation, skills use and training*. OECD. https://www.oecd-ilibrary.org/docserver/2e2f4eea-en.pdf?expires=1610528966&id=id&accname=guest&checksum=D624296D30AAFFAC3813BF62391C971E

Neuberger-Fernandez, L., Barton, R., & Accenture Corporate Citizenship. (2017). *New Skills Now: Inclusion in the Digital Economy*. https://www.accenture.com/t20171012t025413z__w__/in-en/_acnmedia/pdf-62/accenture-new-skills-now-report.pdf

Newman, D. (2020). The human and machine workforce leading digital transformation. *Forbes*. https://www.forbes.com/sites/danielnewman/2020/02/17/the-human-and-machine-workforce-leading-digital-transformation/?sh=146a9cfc7cf5

OECD. (2019b). *Determinants and impact of automation: An analysis of robots' adoption in OECD countries*. OECD, Paris, France. https://www.oecd-ilibrary.org/science-and-technology/determinants-and-impact-of-automation_ef425cb0-en

OECD. (2019a). *The future of work: OECD Employment Outlook 2019*. OECD Publishing. https://www.oecd-ilibrary.org/employment/oecd-employment-outlook-2019_9ee00155-en

OECD. (2011). *Towards an OECD skills strategy*. OECD Skills Strategy. http://www.oecd.org/education/47769000.pdf

OECD. (2013). *The survey of adult skills: Reader's companion*. OECD Publishing. https://www.oecd.org/skills/piaac/Skills%20(vol%202)-Reader%20companion--v7%20eBook%20(Press%20quality)-29%20oct%200213.pdf

OECD. (2018). *The future of education and skills: Education 2030*. OECD (Organisation for Economic Co-operation and Development). https://www.oecd.org/education/2030/E2030%20Position%20Paper%20(05.04.2018).pdf

Oliveri, S. (2020). *These 4 skills can make the world better after COVID-19*. https://www.weforum.org/agenda/2020/08/the-four-skills-to-make-the-world-better-after-covid-19/

O*NET. (n.d.). *O*NET OnLine*. https://www.onetonline.org/find/descriptor/browse/Skills/2.B.4/

Opyt, B. (2019). *Why are soft skills so hard?* Training Industry. https://trainingindustry.com/articles/leadership/why-are-soft-skills-so-hard/

Oschinski, M., & Wyonch, R. (2017). Future shock? The impact of automation on Canada's labour market. *The Impact of Automation on Canada's Labour Market (March 16, 2017). CD Howe Institute Commentary*, *472*. https://www.cdhowe.org/sites/default/files/attachments/research_papers/mixed/Update_Commentary%20472%20web.pdf

Ovanessoff, A., Sage-Gavin, E., & Morvan, L. (2018). *It's learning. Just not as we know it. How to accelerate skills acquisition in the age of intelligent technologies.* (p. 40). Accenture. https://www.accenture.com/_acnmedia/Thought-Leadership-Assets/PDF/Accenture-Education-and-Technology-Skills-Research.pdf#zoom=50

Pajarinen, M., & Rouvinen, P. (2014). Computerization threatens one third of Finnish employment. *Etla Briefs*, *22*, 6.

Palmer, C., & Bolderston, A. (2006). A brief introduction to qualitative research. *Canadian Journal of Medical Radiation Technology*, *37*(1), 16–19.

Parry, E., & Battista, V. (2019). The impact of emerging technologies on work: A review of the evidence and implications for the human resource function. *Emerald Open Research*, *1*(5), 5.

Patscha, C., Glockner, H., Störmer, E., & Klaffke, T. (2017). *Skill and vocational development needs over the period to 2030: A joint situation report by the partnership for skilled professionals*. Federal Ministry of Labour and Social Affairs. https://www.bmas.de/SharedDocs/Downloads/EN/PDF-Publikationen/skill-and-vocational-development-needs.pdf;jsessionid=4894D727033605E621DADC5F2A70A043.delivery2-replication?__blob=publicationFile&v=1

Payton, A., & Knight, G. (2018). *Skills for a global future*. 27th National VET Research Conference "No Frills". https://www.ncver.edu.au/__data/assets/pdf_file/0041/3179885/Skills-for-a-global-future.pdf

Pouliakas, K. (2016). *Rise of the machines: Technological skills obsolescence in the EU*. 15.

Pouliakas, K. (2018). *Determinants of automation risk in the EU labour market: A skills-needs approach*. https://ideas.repec.org/p/iza/izadps/dp11829.html

Rahilly, L. (2020, October 30). *Today's skills, tomorrow's jobs: How will your team fare in the future of work?* https://www.mckinsey.com/business-functions/organization/our-insights/todays-skills-tomorrows-jobs-how-will-your-team-fare-in-the-future-of-work

Rainie, L., & Anderson, J. (2017). The Future of Jobs and Jobs Training. *Pew Research Center*. https://www.voced.edu.au/content/ngv%3A77340

Raj, M., & Seamans, R. (2019). Primer on artificial intelligence and robotics. *Journal of Organization Design*, *8*(1), 1–14.

Rajadhyaksha, A., & Chatterjee, A. (2018). Robots at the gate: Humans and technology at work. *Barclays*. https://www.investmentbank.barclays.com/content/dam/barclaysmicrosites/ibpublic/documents/our-insights/Robots-at-the-gate/Barclays-Impact-Series-3-Robots_at_the_Gate-3MB.pdf

Rallyware. (2019). *70% of jobs will be hybrid by 2029: Are you prepared?* https://www.rallyware.com/blog/hybrid-jobs

Riad, N. (2017). Education for Life: Labor markets are changing, and millennials must prepare and adjust. *Finance and Development*, 16–19.

Rogers, K. (n.d.). *What is systems thinking?* https://bigthinking.io/what-is-systems-thinking/

Russo, A. (2020). Recession and automation changes our future of work, but there are jobs coming, report says. *Wordl Economic Forum*. https://www.weforum.org/press/2020/10/recession-and-automation-changes-our-future-of-work-but-there-are-jobs-coming-report-says-52c5162fce/

Schlogl, L., & Sumner, A. (2018). The rise of the robot reserve army: Automation and the future of economic development, work, and wages in developing countries. *Center for Global Development Working Paper*, *487*. https://www.cgdev.org/sites/default/files/rise-robot-reserve-army-automation-and-future-economic-development.pdf

Schmelzer, R. (2019). How pattern matching in machine learning powers AI. *TechTarget*. https://searchenterpriseai.techtarget.com/feature/How-pattern-matching-in-machine-learning-powers-AI

Schulte, P., & Howard, J. (2019). The impact of technology on work and the workforce. *International Labour Organization*.

Seet, P.-S., Jones, J. T., Spoehr, J., & Hordacre, A.-L. (2018). *The Fourth Industrial Revolution: The implications of technological disruption for Australian VET*. https://www.ncver.edu.au/__data/assets/pdf_file/0019/3161125/The-Fourth-Industrial-Revolution-the-implications-of-technological-disruption-for-Australian-VET.pdf

Servoz, M. (2019). The future of work? Work of the future. *On How Artificial Intelligence, Robotics and Automation Are Transforming Jobs and the Economy in Europe. In AI Report*, *44*, 10–2307.

Shook, E., & Knickrehm, M. (2017). Harnessing revolution: Creating the future workforce. *Accenture strategy*. https://www.accenture.com/_acnmedia/pdf-40/accenture-strategy-harnessing-revolution-pov.pdf

Shook, E., & Knickrehm, M. (2018). Reworking the revolution. *Accenture Strategy*, 1–44.

Siekmann, G., & Fowler, C. (2017). *Identifying work skills: International approaches*. National Centre for Vocational Education Research. https://www.ncver.edu.au/__data/assets/pdf_file/0028/1456660/Identifying-work-skills-report.pdf

Sigelman, M., Bittle, S., Markow, W., & Francis, B. (2019). *The Hybrid Job Economy: How new skills are rewriting the DNA of the job market*. Burning Glass Technologies. https://www.burning-glass.com/wp-content/uploads/hybrid_jobs_2019_final.pdf

Sudhakar, J. (2018). *Transverse skills are the foundation skills for future*. LinkedIn. https://www.linkedin.com/pulse/transverse-skills-foundation-future-ms-jemi-sudhakar/

Taylor, C. (2019). *Robots could take over 20 million jobs by 2030, study claims*. CNBC. https://www.cnbc.com/2019/06/26/robots-could-take-over-20-million-jobs-by-2030-study-claims.html#close

Thought Leaders. (n.d.). *Can you take me higher: Building higher-order thinking skills*. Thinkingmaps. https://www.thinkingmaps.com/higher-order-thinking-skills/

Ton, Z., & Kalloch, S. (2017). *Transforming today's bad jobs into tomorrow's good jobs*. https://hbr.org/2017/06/transforming-todays-bad-jobs-into-tomorrows-good-jobs

Tytler, R., Bridgstock, R. S., White, P., Mather, D., McCandless, T., & Grant-Iramu, M. (2019). *100 Jobs of the Future*. Ford Motor Company of Australia. https://cica.org.au/wp-content/uploads/100-jobs-of-the-future-report.pdf

UNESCO. (2018). *Digital skills critical for jobs and social inclusion*. https://en.unesco.org/news/digital-skills-critical-jobs-and-social-inclusion

Universities UK. (2018). *Solving future skills challenges*. Universities UK, London, England. https://www.universitiesuk.ac.uk/policy-and-analysis/reports/Documents/2018/solving-future-skills-challenges.pdf

van der Zande, J., Teigland, K., Siri, S., & Teigland, R. (2018). *The substitution of labor: From technological feasibility to other factors influencing job automation* (Innovative Internet: Report 5; pp. 1–74). Stockholm School of Economics: Center For Strategy and Competitiveness. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3140364

Vazquez, I., Milasi, S., Carretero Gomez, S., Napierala, J., Robledo Bottcher, N., Jonkers, K., Goenaga Beldarrain, X., Arregui Pabollet, E., Bacigalupo, M., & Biagi, F. (2019). *The changing nature of work and skills in the digital age*. Joint Research Centre. file:///Users/ameliekraft/Downloads/the_changing_nature_of_work_online_v5%20(1).pdf

Vinters, T. (2018). *Automation will change leadership*. https://www.lexology.com/library/detail.aspx?g=f941054f-8dd2-4097-ac4e-5484e07b881b

Vu, V., Lamb, C., & Willoughby, R. (2019). *I, Human: Digital and Soft Skills in a New Economy*. Brookfield Institute for Innovation Entrepreneurship. https://brookfieldinstitute.ca/wp-content/uploads/I-Human-ONLINE-FA.pdf

West, D. M. (2018). Will robots and AI take your job? The economic and political consequences of automation. *Brookings*. https://www.brookings.edu/blog/techtank/2018/04/18/will-robots-and-ai-take-your-job-the-economic-and-political-consequences-of-automation/

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative Intelligence: Humans and AI are joining forces. *Harvard Business Review*. https://hbr.org/2018/07/collaborative-intelligence-humans-and-ai-are-joining-forces

Winde, M., Djabarian, Y., Horndasch, S., Janoschka, O., Lehmann-Brauns, C., Meyer-Guckel, V., Rampelt, F., Raschke, M., Röwert, R., & Schröder, E. (2019). Für morgen befähigen: Hochschul-Bildungs-Report-2020. *Stifterverband Für Die Deutsche Wissenschaft & McKinsey & Company*. file:///Users/ameliekraft/Downloads/hochschul-bildungs-report_2019%20(2).pdf

World Economic Forum (WEF). (2016). *The future of jobs: Employment, skills and workforce strategy for the fourth industrial revolution*. World Economic Forum. http://www3.weforum.org/docs/WEF_Future_of_Jobs.pdf

World Economic Forum (WEF). (2018). *The future of jobs report 2018*. World Economic Forum. http://www3.weforum.org/docs/WEF_Future_of_Jobs_2018.pdf

World Economic Forum (WEF). (2020). *The future of jobs report 2020*. World Economic Forum.

http://www3.weforum.org/docs/WEF_Future_of_Jobs_2020.pdf

Yilmaz, K. (2013). Comparison of quantitative and qualitative research traditions: Epistemological, theoretical, and methodological differences. *European Journal of Education*, *48*(2), 311–325.

Zeira, J., & Nakamura, H. (2018). This new paper has a bold conclusion about automation and unemployment. *World Economic Forum*. https://www.weforum.org/agenda/2018/12/automation-and-unemployment-help-is-on-the-way

Zins, J. E., & Elias, M. J. (2007). Social and emotional learning: Promoting the development of all students. *Journal of Educational and Psychological Consultation*, *17*(2–3), 14.

Zobrist, L., & Brandes, D. (2017). What key competencies are needed in the digital age? The impact of automation on employees, companies and education. *Deloitte*. https://www2.deloitte.com/content/dam/Deloitte/ch/Documents/innovation/ch-en-innovation-automation-competencies.pdf

Z_punkt The Foresight Company. (2014). *The future of work: Jobs and skills in 2030*. UK Commission for Employment and Skills (UKCES). https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/303335/the_future_of_work_key_findings_edit.pdf

Appendix

Appendix A: Interview Guideline (English/German)

Interview Guideline: How is job automation changing the skill requirements of jobs?

Introduction

- Welcome and thank you for your help and participation
- Introduction to the topic
- Assurance of anonymity
- Asking for permission to record the interview

1. Introductory Question: Please briefly describe your professional background and current job role.

2. According to various studies published in recent years, job automation is expected to significantly change jobs and work in general. What is your opinion to that?
    - Which changes in jobs or work tasks do you expect?
        - Potential effects of job automation:
            - Job displacement & Job decline
            - Job growth & Job creation
            - Job transformation & augmentation
    - Do you have concrete examples?

3. In your opinion, which skills or competences can modern automation technologies emulate effectively?
    - With regards to this, how do you think will the capabilities of technology develop within the next few years?

4. In view of the anticipated changes in jobs or work tasks caused by automation, how do you think will the skill or competency requirements of jobs change in the near future?
    - According to your opinion, which kind of skills will experience a decline in their future demand?
    - According to your opinion, which kind of skills will experience a growth in demand?
    - Can you give specific examples?

Conclusion

- We are now at the end of the interview. Would you like to add anything else?
- Are you interested in the interview transcripts and/or findings?
- Thank you for your participation.

Interviewleitfaden zum Thema "How is job automation changing the skill requirements of jobs?"

Einleitung

- Begrüßung
- Vielen Dank für die Mithilfe
- Du oder Sie?
- Einführung in das Thema
- Zusicherung der Anonymität
- Erlaubnis zur Aufnahme des Interviews

- Einstiegsfrage: Würden Sie bitte kurz ihre Tätigkeit in ihrem Unternehmen beschreiben?
- Einleitungsfrage: Laut aktuellen Studien verändert Job Automatisierung die Arbeit/Jobs innerhalb der nächsten Jahrzehnte grundlegend. Was ist Ihre Meinung dazu?
  - Welche Veränderungen sind zu erwarten?
  - Können Sie konkrete Beispiele nennen?
  - Bezug auf die Effekte der Job Automatisierung hinsichtlich Jobs/Arbeitsaufgaben nehmen:
    - Rückgang & Elimination von Jobs (Job decline/displacement)
    - Wahcstum & Entstehung von Jobs (Job growth/creation)
    - Veränderung bestehender Jobs (Job transformation & augmentation)
- Welche Kompetenzen/Fähigkeiten (Skills) können, aus Ihrer Sicht, heutzutage effektiv von modernen Automatisierungstechnologien erfolgreich imitiert/nachgeahmt werden?
  - Wie wird sich, im Hinblick dessen, aus Ihrer Sicht die Leistungsfähigkeit moderner Automatisierungstechnologien in den nächsten Jahrzehnten verändern?
    - Beispiele?
- Im Hinblick auf die erwarteten Veränderungen von Jobs/Arbeit durch Automatisierung, wie werden sich, Ihrer Meinung nach, die Kompetenzanforderungen (skill requirements) von Jobs innerhalb der nächsten Jahrzehnte durch den Einsatz moderner Automatisierungstechnologien verändern?
  - Bei welchen Anforderungen/Fähigkeiten/Kompetenzen (Skills) ist, Ihrer Meinung nach, eine geringere Nachfrage innerhalb der nächsten Jahrzehnte zu erwarten?
  - Bei welchen Anforderungen/Fähigkeiten/Kompetenzen (Skills) ist, Ihrer Meinung nach, eine erhöhte Nachfrage innerhalb der nächsten Jahrzehnte zu erwarten?
  - Welche spezifischen Kompetenzen oder Fähigkeiten werden immer relevanter in zunehmend automatisierten Arbeitsumfeldern?
  - Beispiele?

Abschluss

- Wir sind jetzt am Ende des Interviews. Gibt es von Ihrer Seite noch Anmerkungen?
- Interesse an Transkript bzw. Ergebnissen?
- Vielen Dank für Ihre Mithilfe.

Appendix B: Coding Template

Liste der Codes	Häufigkeit
Codesystem	948
VIOLETT	3
GELB	628
ROT	1
Popular viewpoints regarding the effects of automation on jobs/	0
Technical automation potential	41
Job transformation & augmentation	55
Job creation	12
Job displacement	34
Anticipated future skill trends in the context of automation	0
Combination of different skills/skill categories	19
Skill categories that are expected to grow in relevance due to automation	0
Higher-order/level skills	11
Uniquely human skills	7
Systems skills	10
Social and emotional skills	34
Digital and technological skills	36
Advanced cognitive skills	53
Skill categories that are expected to decline in relevance due to automation	0
Lower-order skills	0
Basic cognitive skills	2
Physical and manual skills	2