# Digital technologies, innovation, and skills: emerging trajectories and challenges

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**Digital Technologies, Innovation, and Skills: Emerging Trajectories and Challenges**

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**ABSTRACT**

In order to better understand the complex and dialectical relationships between digital technologies, innovation, and skills, it is necessary to improve our understanding of the coevolution between the trajectories of connected digital technologies, firm innovation routines, and skills formation. This is critical as organizations recombine and adapt digital technologies; they require new skills to innovate, learn, and adapt to evolving digital technologies, while digital technologies change the codification of knowledge for productive and innovative activities. The coevolution between digital technologies, innovation, and skills also requires, and is driven by, a reorganization of productive and innovation processes, both within and between firms. We observe this in all economic sectors, from agriculture to services. Based on evidence on past technologies in the innovation literature, we suggest that we might require a new set of stylized facts to better map the main future trajectories of digital technologies, their adoption, use, and recombination in organizations, to improve our understanding of their impact on productivity, employment and inequality. The papers in this special issue contribute to a better understanding of the interdependence between digital technologies, innovation, and skills.

## 1. Introduction

Digital technologies permeate and restructure all facets of economic and social activities. In some ways that they are implemented, they disrupt existing activities, while in others they have a more incremental impact and complement existing activities. In some cases, they substitute for existing technologies and tasks, but in others they are complementary. At times, they result in the creation of new activities, services, innovation, and business opportunities. Digitalization is powerful because it not only allows automation but also tracks and stores information and data about tasks and activities, thereby creating a record that can be analyzed and that provides opportunities to improve processes, work organization (Zuboff, 1988), and predictions about future events (Agrawal, Gans, and Goldfarb 2018). The ability to model the analog world digitally has unleashed a wave of both innovation and hype. Widely discussed technologies include the internet of things, blockchains, additive manufacturing, big data, artificial intelligence, cloud computing, and augmented and virtual reality (for one of many listings, see Rindfleisch et al., 2017). Some of them, such as cloud computing, are already realized, others may never become significant, and new combinations certainly will emerge.

The application domains of digital technologies span all sectors, from agriculture and manufacturing to professional services, health services, and beyond. Much popular and academic attention has been paid to the transformational or disruptive implications of digital technologies for businesses (new business models, types of products/services, types of customer experiences, and organizational structures and routines), work, education, and society at large. Organizations and workers might need to adapt or even radically transform themselves to succeed in the continually evolving digital world (Brynjolfsson and McAfee, 2014; Frey and Osborne, 2017; Nambisan et al., 2019; Schwab, 2017). Even changes that seem incremental and gradual and follow the learning processes typically observed for new technologies might ultimately become deeply transformational in ways that are unpredictable ex ante. For instance, the ability to codify human tasks in software has a profound effect on skills and the types of jobs available (e.g., Helper et al., 2021). Skill requirements are changing within and across organizations, industries, and countries and making existing ones redundant or obsolete (Autor, 2015; Autor et al., 2015; Cedefop, 2018).

The time scales and directions of these changes are heterogeneous across technologies, industries, and locations. Multiple technological trajectories, for different digital technologies and applications, may develop, clash, and evolve over time, at a different pace in different industries (Martinelli et al., 2021). Digital technologies also provide the means to reinvent firms, improving the organization and production of goods and services as well creating new goods and services and even transforming innovation routines (Alcacer et al., 2016; Hinings et al., 2018; Nambisan et al., 2017).

The direction of change in the adoption and use of digital technologies at organizations and the adoption of innovations in previous routines can also be affected by unexpected events. For instance, the COVID-19 pandemic forced many in-person events to go online within a very short time. The use of digitalization that previously had a limited impact, such as telemedicine, was massively increased in a matter of weeks (e.g., Mann et al., 2020). Although the adoption of telemedicine implies a "simple" shift from in-person to video consultation, for many regular doctors' visits, the advantages (and potential drawbacks) became obvious immediately, and the earlier routines might not be restored. Changes that might have taken years to be adopted were accelerated by this unexpected event.[1]

In order to better understand the complex and dialectical relationships between innovation, skills, and digital technologies, it is necessary to improve our understanding of the coevolution between

[1] The shift is likely to unleash many changes and innovations concerning how to manage this transformation most efficiently and effectively. There are also likely to be major implications for employment patterns, as there will be significantly reduced demand for receptionists, janitors, and various supplies. A picture taken at home by a high-resolution

the trajectories of connected digital technologies, firm innovation strategies, and skills. Advances in digital technologies are not completely exogenous. Innovation is an outcome as well as a source of digital transformations in the economy and society. Digital technologies require unique skills to be developed as well as different skills to be introduced in production processes, to support new organization of innovating firms, its buyers and suppliers, even as they result in a reconfiguration of the division of labor. These factors also influence the innovation process and the development of new digital technologies. As digital technologies continue to evolve, the skills needed to develop and adopt these technologies also are evolving. In fact, the ability to adapt to this constant evolution suggests that firms and their employees must develop a "meta-skill," which is the ability to adapt existing skills continually or acquire new skills to use the new capabilities afforded by change in the digital technologies.

We illustrate the interdependence between innovation, skills, and digital technologies in Figure 1. The three vertices show the dyadic relationships between the three dynamics, which are usually studied in pairs. The systemic interaction between these three dynamics requires and is driven by a reorganization of productive and innovation processes, both within and between firms. Based on the literature, in this paper, we first illustrate the interconnections between these three dynamics and then

smartphone is becoming sufficient for preliminary diagnosis. New innovations, such as tele-diagnosis equipment could be used.

discuss implications for firm and industry organization, including how these organizational changes influence the three dynamics and their coevolution.

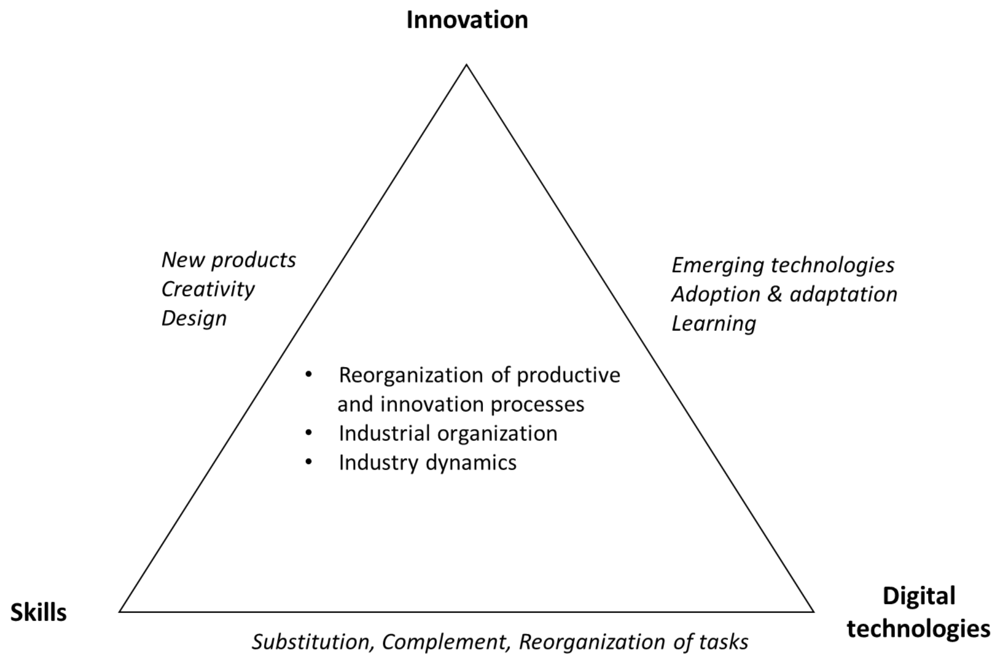



**Figure 1. Interconnections between innovation, skills, and digital technologies**

The remainder of this paper is organized as follows. Building on examples of specific digital technologies, Section 2 explores their interdependence with innovation and skills. In Section 3 we discuss the relationship between digital technologies, skills, and innovation and the reorganization of activities. We discuss how these reorganizations differ across activities in the primary sector, manufacturing, and services. Based on the questions raised by this discussion, Section 4 elaborates three research challenges for gaining a better understanding of the coevolution between innovation, skills, and digital technologies and the relevant impacts. In Section 5, we discuss the contributions toward answering these questions made by the seven papers in this special issue. In Section 6, we offer some implications and suggest a few directions for future research.

## 2. Exploring the Coevolution among Digital Technologies, Innovation, and Skills

The result of von Neumann–based digital computing is the proliferation of individual technologies, ranging from computers and industrial robots, which have been in use for decades, to “intelligent” machines that can “learn” (machine learning). Given the diversity of technologies, not surprisingly, different studies provide different definitions and categorizations of digital technologies. These technologies also differ with respect to the rate at which they have been adopted, by which firms, and how they interact, although overall their impact and continuing momentum are enormous. For example, robotics is a comparatively well-established technology in manufacturing, but, more recently, it has been widely adopted in the services, in particular, retail and warehousing, and, even more broadly, in all kinds of activities, such as answering phone calls (chatbots). The adoption of robotics in manufacturing is highly skewed and mostly adopted by just a few large firms (Acemoglu, Le Large, and Restrepo, 2020; Deng, Plümpe, and Stegmaier, 2020).

One vision of the future of digital technologies, the Industry 4.0 “paradigm,” was introduced by the German government in 2013 and has attracted a great deal of attention (Kagermann, 2015; Lasi et al., 2014). Industry 4.0 envisioned a “smart” factory based on cyberphysical systems that integrate advanced technologies in the physical and digital production systems and allow integration across the data systems of firms and sectors. It was intended to drive the integration of technologies, such as factory automation/robots, data exchange in manufacturing technology, additive manufacturing/3D printing, cloud computing, the internet of things, big data, and AI (e.g., Martinelli et al., 2021). Whereas Industry 4.0 focused on manufacturing, other studies take a broader view of the diffusion of digital technologies and recognize their application beyond manufacturing (e.g., Lusch and Nambisan, 2015).

In Figure 2, we identify some of the most significant digital technologies that are reconfiguring the workplace, when they initially emerged, and their data intensity. These technologies range from those based on data, such as cloud computing and AI, to those with a physical manifestation, such as robots and drones. The most data-intensive technologies in particular are progressing rapidly, based on the dynamic of Moore's law regarding the speed of improvements in processing power. Because their underlying "raw material" is processed data, they can be combined and recombined in ways that enable new applications, which can create new value (Henfridsson et al., 2018). This opens up a seemingly infinite set of options for further recombinations and the initiation of various technological trajectories (Lanzolla et al., 2021). For example, new fruit-picking robots combine robotics with image recognition to determine which pieces of fruit to pick and which to leave for further maturation. Experimentation is ongoing on drones that will not only pick the fruit but also deposit it in the crates for shipping. For another example, drones are being trained to identify different kinds of weeds and spray them with microbursts of pesticide (for a general discussion, see Kenney et al., 2020). These recombinations and the development of task-specific machines and software make digital technologies generative of yet more innovations (Zittrain, 2008).

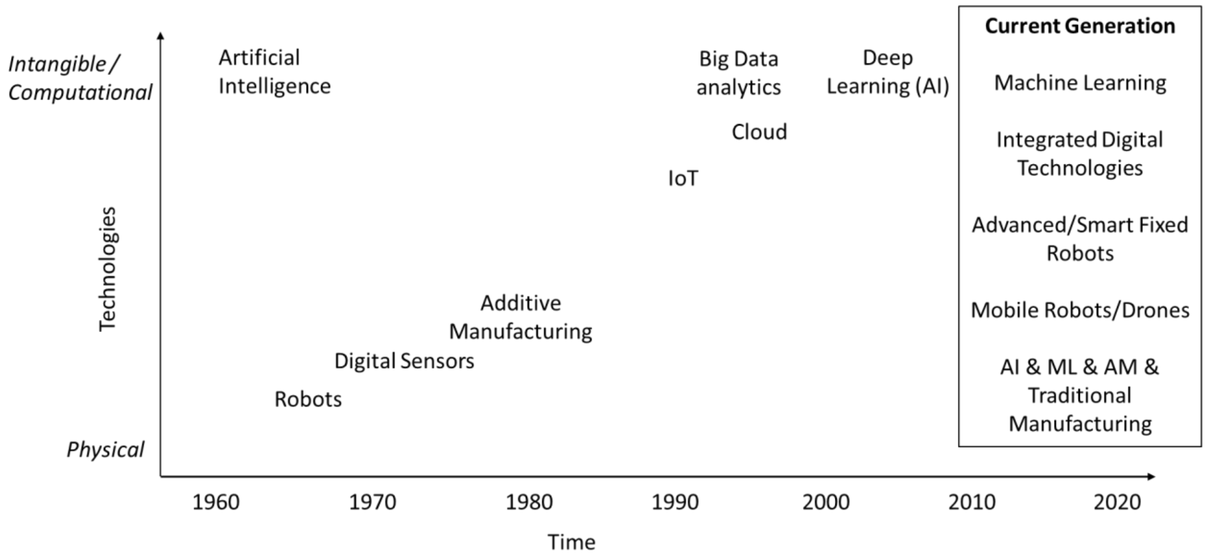



**Figure 2. Digital Technologies: Emergence, Evolution, and Fusion**

To distinguish current from previous waves of automation, Shoshona Zuboff (1988) labeled this digitization process as one in which a machine is equipped with digital sensors. She suggested that by digitizing its operations, its events and activities became transparent to the organization and thus more easily optimized, linked to yet other machines, and reorganized—all according to a logic dictated by computers. These characteristics allow the technology to coevolve with firm innovation and organization in ways that enable the creation of new business models and value propositions (Colfer and Baldwin 2016). As this process advances, new and, at times, unexpected recombinant innovations emerge. This is illustrated in the box on the right-hand side of Figure 2 that shows how these technologies are recombined and integrated, creating yet more innovation.

The interdependence of these digital technologies is confirmed by the adoption patterns. Recent surveys show that although the rate of adoption for many of these digital technologies is relatively low and skewed toward larger firms, it has a hierarchical pattern in which the most sophisticated technologies are most frequently accepted only after more basic applications (e.g., Zolas et al., 2021). Moreover, substantial heterogeneity is seen in the recombination and development of new technologies that cannot be fully explained by adoption data. For example, many firms develop their digital technologies in house for their own use (Montobbio et al., 2020). Early developers and adopters appear to have competitive advantages, and research suggests that the gap between early adopters and laggards is likely to grow (Barth et al., 2020a, 2020b). Presumably, innovation is already underway by these early adopters to integrate and fully exploit the potential of the new technologies. This interdependence between digital technologies and innovation processes makes it more difficult to predict their development and when and where a transformative effect will take hold. Our understanding of the evolution and impact of these digital technologies should improve over time as we acquire more data (Frank et al., 2019).

Overall, it is not yet clear how these digital technologies, all of which are evolving rapidly, will coevolve with the reorganization of tasks within occupations and across firms (Agrawal et al., 2019; Lane and Saint-Martin, 2021). Much of our knowledge about the relationship between digital technologies and skills relies on quantitative research on the adoption of information and communication technology (ICT) (e.g., Autor et al., 1998; Bresnahan et al., 2002) and automation (e.g., Arntz et al., 2017; Bessen, 2019) and the extent to which they replace humans in performing tasks (Acemoglu and Restrepo, 2018).

Skill-biased technological change (Autor et al., 1998; Bresnahan et al., 2002) and, subsequently, routine-biased technological change (Goos et al., 2009, 2014) have been proposed to explain historical patterns in the labor market, such as the relative decline in low-skill workers compared with both high-skill and medium-skill workers at the beginning of the 1980s (Goos and Manning, 2007; Goos et al., 2009; Adermon and Gustavsson, 2015), and the more recent hollowing out of the middle class and middle-skilled routinized tasks, which are susceptible to being performed by machines (Autor, 2014; 2015). Based on this framework, estimates of the impact of digital technologies on employment vary widely. Some views are more pessimistic, i.e., digital technologies will mainly lead to the elimination of some jobs (Acemoglu and Restrepo, 2019; Frey and Osborne, 2017; Korinek and Stiglitz, 2017); others are more optimistic, i.e., digital technologies will mainly improve existing jobs or create new ones (Arntz, Gregory, and Zierahn, 2017; Autor and Salomons, 2018; Felten, Raj, and Seamans, 2019); and still others take a more neutral stance, i.e., the effects will be mixed (Das et al., 2020; Nedelkoska and Quintini, 2018). These studies tend to consider the technologies relatively well defined (skill/routine biased) and exogenous, which is at odds with the coevolution with innovation processes and reconfigurations that they seem to undergo within firms.

The sectors that have adopted digital technologies with the greatest enthusiasm include finance, insurance, mass production, and process industries. Manufacturing is commonly believed to be at the forefront of game-changing technological innovation, but far less attention has been paid to the services. For example, a report on the impact of advanced industrial robotics, additive manufacturing, the industrial internet of things, and electric vehicles suggests that these new technologies are likely to affect employment by displacing workers, but it is hoped that they will also result in an upgrading of occupations, the development of more hybrid skill sets, and a decrease in repetitive routine work (Eurofound, 2018).

Over the past few decades, three main patterns of labor market change occurred as a result of these changes in organization (Eurofound, 2020): (1) upgrading (a linear improvement in the employment structure, with highest employment growth in highly paid jobs); (2) polarization (larger employment growth at both ends of the job–wage distribution, shrinking the middle), and (3) flexibilization (an increase in nonstandard employment, characterized by marginal part-time work, short-term temporary contracts, and on-demand work, often called “gig” work (De Stefano, 2015).[2] For each of these patterns, digitalization appears to have played a role in increasing their prevalence.[3]

The debate over routinized tasks, and what can be automated, harkens back to Polanyi's distinction between “tacit” and “explicit” knowledge. However, the distinction between them has evolved as digital technologies have improved. For instance, what used to be nonroutine and tacit has progressively become standardized, formalized, better understood, and eventually replicated by software and computers and thus has become routine and codified (i.e., explicit). The advances in digital technologies in terms of computational power, availability, and handling of big data to train machines, storage capacity, and machine learning algorithms enable algorithmic processing of what previously were considered nonroutine tasks that required human learning. The occupations affected range from creative and engineering design fields to legal and other professions (Susskind, 2017).

The key to the ability of these advanced digital technologies to undertake what previously were considered nonroutine tasks is not to replicate human processes and thinking (Susskind and Susskind, 2016) but to standardize some parts of the overall task in order to make them amenable to computerized processing. After nonroutine complex (i.e., integrated) processes are broken down in modular components, they become easier to automate. Reducing the degree of complexity and modularizing complex processes (Kauffman and Levin, 1987; Simon, 1969, 2002) enable machines to replace or expand and complement human capabilities (O’Donovan and Smith, 2020).

[2] There is ample evidence for this digitalization-enabled work, even in cases, such as Uber, at least some of the workers appreciate the flexible arrangements, despite the low pay, precarity, and inability to support a family on the basis of the income. Similarly, in IT-enabled gig work, such as that provided by Upwork; some number of the workers find the work convenient and attractive. In more skilled tasks, it has been demonstrated that some workers choose to work on gigs, rather than accept full-time employment (see, for example, Barley and Kunda 2011). Thus, while the work can be seen as exploitative, even among the workers there appears to be no uniform sentiment.

[3] We do not attribute all of the increased prevalence of these types of contractual arrangements solely to digitalization and thus ignore the role of politics and the neoliberal ideology, see, for example, in the case of the US, Weil (2014).

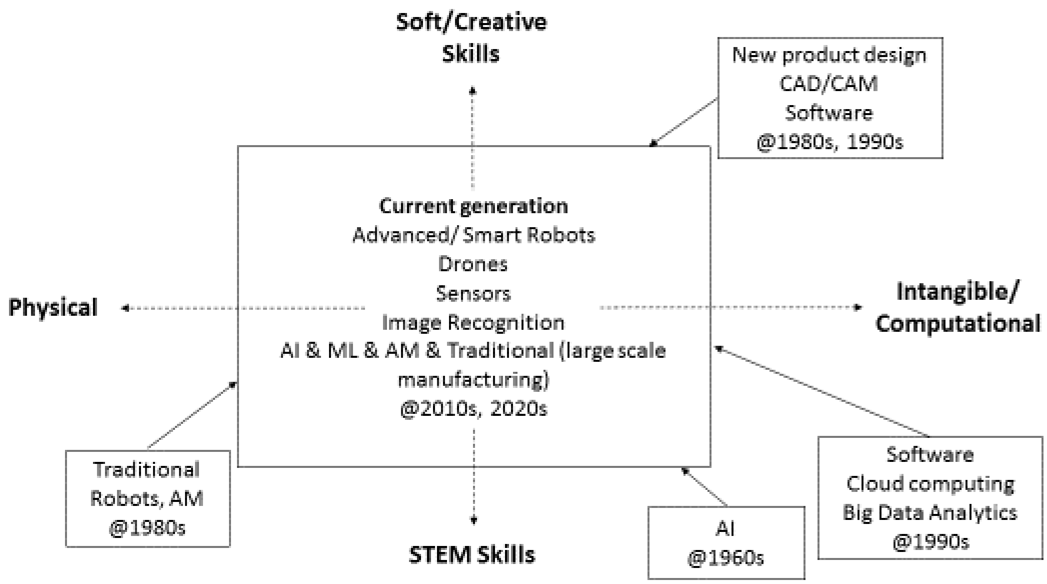
Alongside the new dynamics of substitution between machines and workers performing non-routine cognitive tasks, new dynamics of complementarity among tasks are likely to emerge and become more important, especially because creative tasks, a large subset of nonroutine cognitive tasks, have become more important as the fourth industrial revolution unfolds (Schwab 2017; Pedota and Piscitello, 2020). Machines can complement people in performing tasks that require processing massive amounts of information and data, thus supporting the experiential and emotional judgment of professionals, such as doctors and lawyers. For example, a medical diagnosis of skin cancer based on dermatological images, which use the results of biopsies, can employ AI-based software with higher diagnostic accuracy than trained physicians (Esteva et al., 2017), though computers and people make different types of mistakes (Brynjolfsson and Mitchell, 2017).

Other activities are more difficult to decompose into codifiable and automatable tasks. For instance, tasks that require the recognition of emotions and formulation of a response to them are more difficult to codify in the current state of digitalization. If this is the case, then social skills should increase in importance (e.g., Autor et al., 2002; Brynjolfsson and MacAfee, 2014; Deming, 2017). Paul Deming (2017) suggests that possessing interpersonal and social skills has higher returns than STEM skills.

The direction of progress in machine learning is crucial in this debate, because it will determine which activities and tasks will be liable to replace people with technology (Brynjolfsson and Mitchell, 2017). AI algorithms are increasingly competent at performing specific tasks that have traditionally required human expertise, with emerging applications in medicine, law, transportation, scientific discovery, and other industries (Esteva et al., 2017; Wilder et al., 2020). As the technology coevolves with firm innovation and skills, the extent to which they will replace/complement human occupations is still unclear. Adopting a task-based perspective, Acemoglu et al. (2020) study AI adoption through firms' posting of vacancies that require workers who specialize in AI-related activities. They find that firms that hire AI-proficient workers replace older skills with new skills, modifying their task structure when they replace tasks that were performed by humans, and find no evidence of complementarity between human and AI tasks (although they do not find any employment effect at the industry level). Felten, Raj, and Seamans (2019) study progress in AI tasks (measured by the Electronic Frontier Foundation [EFF] AI Progress Measurement dataset) in relation to the various abilities that characterize the jobs listed in the O*NET (the US Department of Labor's evolving list of occupations). They use this relationship to study the effect of advances in specific AI technologies on different occupations (Felten, Raj, and Seamans, 2019). They find that the occupations that are more affected by advances in AI have increases in employment; the more this is the case, the more automated the occupations are. They interpret their result as an increase in complementarity between AI and human skills, especially in firms that were already on an automation trajectory, which is augmented by AI. By connecting AI patent descriptions to the occupational descriptions in O*NET, Webb (2019) uses a slightly different strategy to connect AI to tasks and finds that, in contrast to earlier rounds of automation related to software and robots, AI may be able perform tasks that previously were considered highly skilled.

Building upon Figures 1 and 2, it is important to consider the convergence and fusion of characteristics of digital technologies and skills, depicted in Figure 3. The horizontal axis shows the characteristics of digital technologies, as a spectrum that goes from fully tangible or physical to completely intangible or computational. On the vertical axis, we show the characteristics of skills ranging from STEM to soft skills (including creative, interpersonal, and social skills), which are related to these technologies. No technologies are in the top-left quadrant, combining physical technologies and soft skills; however, this set of skills is gaining importance in the current generation of digital technologies. Figure 3 illustrates the integration of early generations of digital technologies into the current generation of digital technologies, spanning the full range of characteristics (from physical to intangible) and skills (from STEM to soft).

**Figure 3. The Convergence of Digital Technologies and Skill Characteristics**




## 3. The Reorganization of Production and Innovation Processes

This coevolution of digital technologies, innovation, and skills affects the ways in which firms organize activities within and between them (Hitt, 1999). Here we give some examples, distinguishing between primary, manufacturing, and service activities.

Digitalized activities appear to be particularly placeless, in that the work can be done anywhere with an internet connection and a computer. In the first decade of the 2000s, it appeared that countries with low labor costs, such as India and the Philippines, would benefit the most from this digitally enhanced flexibility (Kenney et al., 2009). In retrospect, the apocalyptic visions of offshoring work have not yet been realized, perhaps because the cost differentials became less attractive over time and because many firms did not want to embark on process and organizational restructuring, possibly because in the meantime much of the work had become sufficiently routinized that it could be performed with automation.

The development of additive manufacturing (AM) technologies has made the calculation on how, where, and what to produce more difficult. For example, some have argued that AM results in a clash between the classes of heuristics that favor simplicity and those that favor complexity. In the case of traditional manufacturing, which is optimized for modularization, "simple is better" is a powerful heuristic, which contrasts with the "complexity for free" motto of AM. Thus, AM and traditional manufacturing may be substitutes in some instances, but they are also complements, as AM is used for prototyping or production in small batches, whereas traditional mass production (e.g., using advanced, sophisticated, AI-controlled robots) is used for production in larger volume (Pedota and Piscitello, 2021).

One of the putative benefits of Industry 4.0 was the belief that current offshoring and relocation strategies would be reconsidered. Although the adoption of Industry 4.0 technologies may have reduced the pace of delocalization to lower-cost countries, it is still too early to observe a positive impact of increasing digitalization on reshoring (Ancarani and Di Mauro, 2018).[4]

More recently, platforms for contracting gig workers have emerged and perform the role of intermediary between the contractor and contractee. These platforms were expected to enable outsourcing and offshoring of a variety of tasks (e.g., Hong and Pavlou, 2017). Although these gig

[4] Given the difficulties that many countries faced with global supply chains during the 2020-21 COVID-19 outbreak, some are predicting that this will trigger reshoring (Barbieri et al., 2020).

work platforms initially grew rapidly, their growth seems to have slowed, if one can generalize from the revenue of the largest among them, Upwork. Like offshoring, platform-organized gig work is a digitally enabled method of hiring labor. However, it is possible that in the long run much of this outsourced work will be automated. Although, in principle, online outsourcing platforms provide ubiquitous access with no geographic constraints, country differences continue to matter even in software development and IT services (Carmel and Tijia, 2005).

Another fundamental development due to digitalization is the introduction and increasing economic and social centrality of online digital platforms (Kenney and Zysman 2016; Van Dijck 2013; Kenney et al., 2020). Online platforms are restructuring business sectors and firm operations for an increasingly large percentage of the workforce and thus increasing their vulnerability to reorganizations enabled by adoption of these platforms. We know little about which skills affect the ability to earn an income through a platform. In the case of Uber, Deliveroo, and other related transportation platforms, these skills may be minimal. However, a successful Instagram influencer or YouTuber certainly has developed skills, though they are quite different from previous skills. Platforms such as the Apple Appstore and Google Play provide resources, such as software development kits, application programming interfaces, and access to a large number of potential customers for entrepreneurial innovators, but we know little about the skills that these "platform-dependent entrepreneurs" possess and require to successfully sustain their precarious income (Cutolo and Kenney, 2021; Cutolo et al. 2021).

These changes caused by digitalization are illustrated by changes in services that are as intrinsically human as answering a customer query at a call center. Only fifteen years ago, nearly all the activities related to answering a verbal customer query were handled by people, and cost reduction was achieved by offshoring to a lower-cost developing country (see, e.g., Dossani and Kenney, 2007). Today, the initial contact is handled with voice recognition software (i.e., a service “bot”) that locates the customer’s account and offers to provide various types of information or to route the call to the appropriate department.

To summarize, digital technologies and skills are increasingly intertwined, integrating complementary physical, intangible, and computational technologies that require multiple and varied skills, from STEM to interpersonal and social skills.

## 4. Three Challenges

As digital technologies coevolve with firm innovation and skills, and firm reorganize their activities, the short review above leads to more questions than answers about their impact on economies and societies. We summarize these questions in terms of three research challenges:

1. Enhancement of understanding of the main future trajectories of digital technologies
2. Increasing understanding and improving data about the adoption, use, and recombination of digital technologies
3. Assessment of their impact on productivity and inequality.

Building on Schumpeter (1939) and Kondratiev’s theory of long waves, Chris Freeman stated that different historical periods (following the first Industrial Revolution) are led by the development and diffusion of fundamental technologies that shape economies and societies (Freeman, 1982, 1991). The latest of these revolutions can be dated to the 1970s, when ICT began to be adopted more generally (Freeman and Louçã, 2002; Freeman and Perez, 1988). Although there is little doubt that ICT has changed industries, production organization, the process of work, the types and characteristics of employment, and the requisite skills (Bresnahan and Trajtenberg, 1995), the discussion in Sections 2 and 3 shows that contemporary digital technologies only partly follow the earlier patterns in which alternative, competing technologies were developed until a dominant design emerged, after which the pace of change slowed and involved mostly process and incremental innovations.

Although the computer industry has exhibited some life-cycle characteristics (Malerba et al., 1999), in many respects, it has violated them, as with each new wave of digitalization, more computers are deployed, and they display remarkable new capabilities. This is largely because of Moore's law, which postulated a log-linear relationship between circuit density, an ever-lower cost per transistor, and relatively predictable, yet astonishingly rapid advances in computing power over time.

This increase in data processing capacity created continual new opportunities for innovation, as some things now could be represented digitally that never could before. The key unknown in this technological advance is what the constantly increasing processing power would make feasible, as software transforms processing power into applications in the real world. For example, as recently as a decade ago, a self-driving car was improbable because the ability to sense and process all the necessary variables in the environment was not yet developed. Thus, at the time, the skills a human driver could display were impervious to replacement as well as automation (Autor et al., 2003). In 2021, some of individual skills, such as collision detection and lane-change warnings, can be performed by automobiles, though human monitoring and, at critical moments, human decision-making remain necessary. The advent of fully autonomous driving represents the automation of the entire activity—unless and until, of course, those vehicles confront entirely unpredictable environmental conditions that its AI cannot recognize and handle.

The first challenge that we face is understanding and predicting the trajectories of digital technologies, due to the complex and nonlinear relation and interdependence among digital technologies, organizations, and skills (Archibugi, 2017; Arthur, 2009; 2013). Digital technologies are constantly evolving and do not seem to have settled into a well-defined trajectory yet. Therefore, we seem to be in the midst of an exploratory phase of a new technology, which makes it difficult to predict the next emerging technology or even how it will be defined (Chiarello et al., 2018). In their first AI index report, Shoham et al. (2017, p7) stated: “Without the relevant data for reasoning about the state of AI technology, we are essentially ‘flying blind’ in our conversations and decision-making related to AI.” Despite temporary signs of convergence and “cooling down” of the AI trajectory (Klinger et al., 2020), the wide range of potential applications, current low rates of adoption, and numerous opportunities for entrepreneurs to enter the market with new business models (Autio et al., 2018) may require us to revisit our understanding and models of past technological revolutions, in order to understand the future development of digital technologies. The various digital technologies are evolving at different rates and following different trajectories. Although it is too early to call them revolutionary, some of these technologies have the potential to become so. However, at present they can be differentiated, as some show the characteristics of general purpose technologies (e.g., cloud computing), whereas others appear to have a limited scope and thus can be understood as enabling technologies (e.g., 3D printing) (Martinelli et al., 2021).

The second and related challenge concerns the fact that, although we have seen massive adoption of earlier digital technologies, such as computers and computer-controlled machines, the extent to which more recent waves of digital technologies and automation are being adopted is unclear. For instance, the Digital Technology Module of the 2008 United States Census Bureau Annual Business Survey (table 3a) shows that, in the US, technologies such as augmented reality, autonomous vehicles, machine learning, and machine vision software have been adopted by between 0.9 and 4.5 percent of the firms, though this includes those that are merely testing them (see also Vannuccini and Prytkova, 2020). In Europe, Deng, Plümpe, and Stegmaier (2020) ascertain from data in the IAB Establishment Survey that in 2018 only 1.55% of German companies had adopted robots. Similarly, the

AI index 2019 Annual Report (Perrault et al., 2019) shows that the industry with the largest share of AI-related jobs, information, had only 2.4% of the AI-related vacancies. Of course, these are only estimates, and firms may not even be aware that they are using the outputs of AI analysis. Consider, for example, a firm that is advertising on Google Search or YouTube. The target of its advertisement may have been chosen with a machine learning algorithm, thus unwittingly they are users. By paying for the advertisement, is the firm using AI? As with all intangibles, if AI is embedded in software, but is not a "physical thing," then it is difficult to measure its adoption, even though it may be substantial (Marcus and Davis, 2019). A fundamental difficulty in measuring the adoption and diffusion of digital technologies is that they have become increasingly intangible or embody elements that are intangible and therefore require data about the value of the transactions involved in accessing a service or the technologies (e.g., a software), which is complicated to capture.

If, as it seems, adoption of new digital technologies is low, why is that the case? Are firms waiting to see how digital technologies develop? Are there too many different technologies that have not yet fully evolved or, perhaps, are changing too rapidly? Is the technology moving too rapidly for firms and workers to adapt to new routines and skills?

The third challenge concerns the difficulty of assessing the impact of digital technologies (including on occupations, as the variations in predictions suggest), unless we improve our ability to study their evolution and adoption. At the aggregate level, since the digital technological revolution, high-income economies have experienced a secular slowdown in productivity growth (Baldwin and Teulings, 2014; Gordon, 2015). Although this may be linked to measurement issues in the prevalent service industries, the reduced gross domestic product per capita growth rates suggest that, unlike in earlier technological revolutions, well-being, measured in economic terms, is not growing. Stimulated by the ICT productivity paradox in the 1980s, the adoption of new technologies is not sufficient for increased productivity—it has to be accompanied by transformations in the firm, jobs, and skills (Brynjolfsson et al., 2017).

In the few decades since the digital revolution began, productivity growth has continued to decline, on average. It has been argued that, although average productivity growth has declined throughout the digital age, except during the financial crisis, the top performers have experienced sustained productivity growth (Andrews et al., 2016; Haldane, 2017). This again raises the possibility that only a few firms can successfully integrate digital technologies, whereas the average firm cannot do so effectively. Presenting an alternative explanation, Brynjolfsson and Collis (2019) argue that digital technologies may be having a negative effect on productivity growth because they offer so many "free" goods and services. As noted in the example above, the productivity created by Google Search, Maps, and YouTube is captured only in the advertising served to users, as the services are free. Similarly, smartphones now have high-quality cameras, watches, compasses, fitness monitors, and many other products/services at a comparatively low price. Moreover, new apps appear constantly and can be downloaded at a very low or even no cost. Thus, even though the true value of the goods and services the consumer received increased, productivity may have dropped.

The digital age has also been accompanied by a steep increase in inequality (Atkinson, 2015; Piketty, 2014), which has been explained in many ways. For example, labour compensation (Karabarbounis and Neiman, 2013) and unionization (Freeman, 2007) have declined, but the compensation of top earners has dramatically increased (Atkinson, Piketty, and Saez, 2011), as has firm size (Mueller, Ouimet, and Simintzi, 2017) and industrial concentration (Autor et al., 2020). Some researchers have found that differences between firms explain two-thirds of the earning variability across workers (Card et al., 2018; Song et al., 2019), suggesting that this outcome is based, in part, on interfirm competition. How much of this is directly related to digitalization is difficult to measure, although researchers have found a higher concentration in patenting (Forman and Goldfarb 2020) and that AI adoption may have increased the concentration of intangible assets in fewer firms (Rock 2019; Tambe et al. 2019). Inequality is also observed geographically. For example, Bloom et al. (2020) study the geographical development of new technologies, primarily but not exclusively digital, and their accompanying employee skill bases. They found that, as employment in these new technologies grew, it was initially concentrated in local hubs, before spreading geographically. Yet the initial hubs retained a disproportionate share of employment, particularly in the most desirable highly skilled positions.

If digital technologies keep evolving and do not settle into well-defined paradigms (Dosi, 1982), definitively measuring their recombination, adoption, and use is likely to remain difficult. We need substantially more evidence, at the firm, sector, and country level, to better understand how digital technologies are evolving and how firms, workers, and their routines and skills coevolve with them. This conclusion aligns with the call voiced by policy makers, academics, and other stakeholders for more and better data that can create insights into the implications of these technologies for economies and societies (National Academies of Sciences Engineering and Medicine, 2017; OECD, 2017; Raj and Seamans, 2018).

The papers in this special issue address some of these challenges directly.

## 5. The Papers in the Special Issue

The papers in this special issue offer significant insight into the challenges identified above but also suggest that there is ample room for more research as we seek to understand the rapidity with which digital technologies are evolving and how they are transforming work.

The first two papers discuss the second and third challenges, respectively, as they explore new ways to measure firm investment in capital that increases digitization (Harrigan, et al., in this issue) and automation (Domini et al., in this issue), and study their impact on employment. Harrigan et al. (in this issue) explore how an increasing share of workers with STEM skills and experiences (“techies”), associated with an increase in digitalization, changes the composition of employment at a firm. They show that techies contribute to driving technological change within firms, resulting in greater job polarization within industries, rather than within the firm. This is because of the recomposition within industries (firms with more techies and digital technologies increase their market share).

Domini et al. (in this issue) employ firm transaction data to measure changes in automation due to investment in automation-intensive capital goods. They then study the impact of these automation “spikes” on employment. In contrast to Harrigan et al., they find that capital investment does not seem to change the composition of labor (i.e., the techies are not complementary to capital), but, in line with Harrigan et al., they see that, after automation spikes, overall employment at automating firms increases. So, consistent with Harrigan et al., they claim that automation helps increase the focal firm’s market share (Acemoglu et al., 2020), and the impact on employment is negative at the industry level.

As discussed earlier, technology, organizations, and skills co-evolve. The paper by Cirillo et al. (in this issue) focus on the specific relationship between technology and skills. Employing an original dataset on occupations in Italy in the period 2011-2016, they analyze the relationship between digitalization, task routinization, and employment. They find that “digital occupations” (i.e., activities that explicitly involve digital technologies) are not necessarily associated with routinized occupations and that, although employment in digital occupations is growing, jobs in routinized occupations tend to decrease.

Discussing the challenge of attaining a better understanding of the relationship between the evolution of digital technologies, organization, and skills, Goos, Rademakers, and Röttger (in this issue) analyze data on workers collected before and after a plant closure to examine what happens to redundant workers. They show that workers who engaged in routine-intensive tasks, in contrast to their peers who performed less-routinized tasks, struggled to find employment at new factories. And workers who had less-routinized jobs but worked at older factories could not find jobs of similar quality, suggesting that their learning at an older factory did not prepare them for working with changing (digital) technologies in new factories.

The question of which skills workers should develop to keep up with increasing digitalization is somewhat vexatious. Two papers in the special issue present significant evidence that is relevant to this question, addressing the challenge of achieving a better understanding of the evolution of digital technologies, organization, and skills, from the perspective of skills. In a cross-country data setting, Falck et al. (in this issue) show that workers with higher ICT skills earn more than their peers with lower ICT skills and gain experience working with more abstract content (i.e., less routinized and using more advanced digital technologies). Further light on these issues is cast by Black et al who use data from a survey of US high school graduates in 1982, at the inception of the digital revolution. They found that the educational experience that was most important in preparing them for a labor market in which they would need to use and learn new digital technologies, was taking courses in advanced mathematics. Those who did so were more likely to find better-paid jobs, better able to adapt to technological evolution, and more likely to be employed in STEM occupations.

The next paper in the issue addresses the third challenge, the role of digital technologies in the economy and society. Neil Foster-McGregor and Bart Verspagen (in this issue) construct different trade scenarios to study the role of trade relations between countries (including offshoring) in the risk of job replacement by automation in any of those countries. In contrast to the micro-level evidence described by Harrigan et al. (in this issue), they find that a country’s sectoral structure largely explains, the risk that its jobs may be replaced by automation, i.e., automation risk varies more between sectors than within them, across countries, and this depends on the composition of the country's industrial base. They find a negative relationship between the risk of automation and labor productivity. Further, they find that trade increases the automation risk for high-productivity European countries, which is caused by trade between European and non-European countries. These European countries do not offshore automation risk but, instead, import it. This risk is concentrated in manufacturing, trade, transport, and finance. In other words, in high-productivity countries, trade (and offshoring) seems to shift the structure of employment toward activities that are more likely to be automated.

## 6. Conclusions

The large discrepancies in the literature in estimating the potential impact of automation and some digital technologies on employment suggest that predicting the skills needed for future employment is filled with uncertainty. Digitalization is often more about the displacement and deep transformation of activities and their organization than about a simple one-to-one replacement of jobs. These transformations are often unforeseen and coevolve with innovation routines and skills. For instance, whereas existing skills are threatened by innovation, and the repetitive nature of tasks increased somewhat, as did the use of software, an examination of the changes in the O*NET occupational skills from 2005 to 2015 found only modest changes in occupational skills (Freeman et al., 2020).

One of the difficulties in predicting the impact of digital technologies on skills is their plasticity and the ease of introducing and diffusing new software. This means that a broad and continuous wave of constant experimentation is underway as software becomes the core of nearly every activity. In Garud et al.'s (2008) reading, software is "incomplete by design" and thus open to constant revision.

This can be seen in many industries. For example, farming is being transformed by digital technologies, so simply training farmers to program farm machinery will not halt the displacement of farmers or farm workers. It is more likely that the farmer (owner) will become a higher-level decision-maker about when to upgrade software and equipment, a decision that requires an understanding of accounting as much as software skills (Kenney et al., 2020). The other impact of automation may be that it will allow farmers to reduce the number of employees hired by replacing them with a combination of hardware and software. The most difficult task for farmers, and thus a skill that they will have to learn, is determining when the software is making bad decisions or recommendations.[5] The difficulty of responding to some types of technological change in very skilled professions can be illustrated by the case of airline pilots who are unlikely to be able to ward off competition from drones through obtaining more advanced training as pilots or learning to write software. It is easy to agree that everyone should be a lifelong learner, but the question is: what should everyone be learning, and what is the likelihood that doing so will lead to employment enabling a middle-class income?

The already turbulent and unpredictable evolution of digitalization was made even more uncertain by the COVID-19 pandemic. As the preparation of this Special Issue proceeded, almost overnight the pandemic changed the physical location of many types of jobs, as those who could work remotely, from home, were told to do so. This radically disrupted the physical organization of work, as meetings and other in-person service activities were performed online. The pandemic accelerated the

[5] The automation literature has little consideration of how the software may be programmed to favor particular actors and thus express the desires of its programmers. Consider, for example, failure-prediction sensors on a piece of machinery. These can be vitally important in preventing dangerous or costly equipment breakdowns. Of course, they could also be programmed to predict failure earlier than necessary, thereby increasing replacement costs and the profits of the equipment maker.

need for digitalization to enable organizations to continue functioning in the short term as well as increase resilience in the long term. It created a further impetus to study the impact of digitalization on the supply of and demand for skills, the mismatch in relevant skills, shortages of skilled workers, and related needs (Fink, 2020).

The pandemic has had a profound impact on all types of work. For example, performing some kinds of work offsite was made possible with digital technologies such as Slack, Zoom, and Ding Talk (China). Like any mass adoption of a new communication medium, this one certainly changed some employee skill sets, career paths, and created entirely new innovation paths. It is uncertain which of them will survive/expand in the post-pandemic period, but business exploration in many organizations was initiated during the pandemic. In addition to affecting services, the pandemic altered physical production and distribution, as factories and warehouses became an important locus of disease transmission, creating increased pressure for automation (Aratani, 2020; Bunge and Newman, 2020).

This special issue was produced to encourage more research that would contribute to a better understanding of how digitalization affects innovation and skills, by improving our understanding of the coevolution between digital transformation, innovation routines and processes, and changes in the skills required to innovate, learn, and adapt—and how these relationships help transform the organization of firms and industries. The papers in this issue present relevant findings on understanding these three dyadic relationships. To address the challenges laid out in Section 5, we call for future research that incorporates the endogenous features of these three dynamics (digital technologies, innovation, and skills). This is probably best achieved by combining multiple or cross levels of analysis, embracing ideas and concepts in multiple disciplines, to define a new set of stylized facts on how innovation practices are being transformed, with their implications for work, jobs, and skills.

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