Eurasian Business Review
https://doi.org/10.1007/s40821-026-00352-y

REGULAR ARTICLE

Understanding the skill provision of the I4.0 digital transformation: evidence from Italian companies

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Received: 16 August 2025 / Revised: 10 February 2026 / Accepted: 7 March 2026

Abstract

This study aims to assess how the adoption of new digital/Industry 4.0 technologies has spurred the demand for both technical and business skills, and whether such skill requirements are met through hiring and/or training. To this end, we use a representative sample of about 950 Italian companies that took part in both waves of a unique survey. We find that the implementation of Industry 4.0 technologies is associated with an increase in both technical skills and business skills. Moreover, significant heterogeneity emerges when we separately consider software, hybrid and machine-based technologies, as well as when we distinguish between hiring and training needs. Specifically, we observe that technologies with a strong software component are more closely associated with business skills, which are mainly sourced through hiring; conversely, hybrid technologies (e.g., IoT) are more closely associated with the demand for new technical skills, which are mostly integrated through training. These findings may help enhance the match between labour demand and supply, especially in this particularly uncertain and complex scenario.

Keywords Digital technologies · Industry 4.0 · Technical skills · Business skills · Training

JEL Classification D22 · J21 · O33

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Published online: 21 April 2026

1 Introduction

The consequences of technological change for labour demand have long been the object of study and debate. However, the advent of the Fourth Industrial Revolution, which is characterised by unparalleled pervasiveness, speed and impact on economic systems, has reignited interest in the implications of technological progress for human capital requirements. In particular, the ongoing digital transformation has underscored the need to identify the competencies required to cope with this fast-changing, uncertain scenario. A better understanding of such skill needs would allow firms to make wiser investments in human capital to support the successful exploitation, implementation, and maintenance of advanced technologies. At the same time, individuals who need to strengthen their existing skills (upskilling) and/or broaden their skill set (reskilling) could make more informed decisions about enrolling in education and training courses. Finally, policymakers could design more effective policies and incentives aimed at prompting companies to promote training activities, and encouraging workers to take part in them.

To explore the impact of technologies on skill demand, several studies within the well-established Skill-Biased Technical Change (SBTC) framework have proxied workers' skills with their level of formal education; for instance, within the mainstream SBTC literature, the number or share of high-skilled workers is often measured by the proportion of employees with a college degree. However, recent research has increasingly adopted more direct measures—such as survey-based indicators—and has scrutinised a broader range of skill types (e.g., Gathmann et al., 2024; Hecklau et al., 2016). Specifically, in recent years, a growing literature has investigated the skill requirements of the technologies associated with the Fourth Industrial Revolution, which are often referred to as new digital technologies or Industry 4.0 (I4.0) technologies.[1] This relationship between technology adoption and skills has been the object of both case studies (e.g.,Cimini et al., 2021; Colombari et al., 2024; Kannan & Garad, 2021) and quantitative analyses (e.g., Cirillo et al., 2024; Huang, 2024; Pedota et al., 2023), from which it emerges that the implementation of new digital technologies has fostered the provision of different skill types, including "soft" skills. Additionally, various quantitative contributions investigate one or both of the channels of skill provision, i.e., hiring and/or training. Most of them find that the adoption of I4.0 technologies spurs the implementation of training aimed at strengthening or introducing the skills required by such technologies; additionally, technology adoption can benefit employment, which, in some analyses, is split into different groups of workers according to their education level or the main type of task required by their job position.

Despite providing robust evidence on this subject, most of the existing quantitative studies present at least one of the following limitations: they look at a narrow array, or even at only one type of technology (e.g., Jiang et al., 2024); they do not simultaneously analyse the two mechanisms of skill provision (e.g., Pedota et al., 2023); they do not specifically address endogeneity concerns (e.g., Gathmann et al.,

[1] Throughout the paper, we interchangeably use, unless otherwise specified, the terms I4.0 technologies and (new) digital technologies.

2024); they account for workers' heterogeneity based on formal education level and macro-type of job but without thoroughly investigating the types of skills underpinning such labour market flows (e.g., Cirillo et al., 2024). Finally, although some scholars also assess the potentially different implications of distinct categories of I4.0 technologies (e.g., Cirillo et al., 2024; Pedota et al., 2023), evidence of the presence of heterogeneous effects on employment outcomes and skill requirements associated with different technology bundles is still limited. More in general, research on the skills boosted by the digital transition remains fragmented, often case-specific, and only loosely connected to the related debate on employment and training. In particular, it is still unclear which types of skills are associated with the adoption of new digital technologies, and whether these skills are primarily acquired through hiring and/or training. To the best of our knowledge, this is the first analysis to examine, within a single framework, technology adoption and skill requirements across different types of Industry 4.0 technologies and skills, while distinguishing between external (hiring) and internal (training) channels for skill acquisition.

To fill this gap, this work examines how the adoption of digital technologies prompts firms to introduce new skills. Specifically, we focus on two broad skill families—technical skills and business skills—and explore the heterogeneity in the relationship between technology and skills across three major categories of digital technologies. Then, for each combination of technology category and skill type, we investigate whether firms meet their skill requirements through hiring and/or training.

To identify the two skill types and the corresponding provision mechanisms, we rely on data from a unique survey that we administered to a sample of Italian firms at the end of 2019 and again three years later. To classify the selected technologies (identified through the survey) into macro-categories, we draw upon taxonomies used in previous studies (e.g., Balsmeier & Woerter, 2019; Calvino et al., 2022; Pedota et al., 2023), as well as our understanding of the key characteristics of these technologies. In doing so, we define three categories, namely, software technologies, hybrid technologies, and machine-based technologies.[2]

Previewing the main findings, our regression analysis on 953 Italian firms (observed in both the waves of our survey) reveals that the adoption of I4.0 technologies is associated with the acquisition of both new technical and business skills, although the latter is contingent upon the demand for new technical competencies. A more nuanced and heterogeneous picture emerges when we distinguish among different types of technologies and when we split skill acquisition into its hiring and training components. Specifically, technologies with a strong software nature are more

[2] The category of software technologies includes CRM, ERP, cybersecurity, and cloud computing; hybrid technologies are represented by Internet of Things (IoT), Big Data Analytics, and Augmented Reality, while the group of machine-based technologies encompasses I4.0 robots and additive manufacturing. Unlike most of other classifications, which generally group technologies into two main categories, we decide to create an intermediate category ("hybrid technologies") encompassing those technologies that present features partly ascribable to software technologies and partly to hardware/machine-based technologies. For instance, we include in this category the Internet of Things, which previous studies have regarded either as a software technology (e.g., Calvino et al., 2022) or as a hardware/automation technology (e.g., Balsmeier & Woerter, 2019). This is consistent with Pedota et al's (2023) assertion that IOT takes part in both categories in light of its hybrid digital-physical status. We check the robustness of this categorization through a factor analysis (see Sect. 4.2.4 and Appendix 3).

closely associated with business skills, which are primarily acquired through hiring. In contrast, hybrid technologies (e.g., IoT) are more strongly linked to new technical skills, mainly sourced through hiring, alongside a smaller demand for business skills, which are integrated primarily through training. Machine-based technologies, on the other hand, are not significant predictors of firms' efforts to upgrade their skill sets, likely because of their labour-saving nature. These findings remain robust across various model specifications and sensitivity checks.

The balance of this study is organised as follows: Sect. 2 reviews the relevant literature and presents the research hypotheses; Sect. 3 introduces the data and the regression model; Sect. 4 illustrates the results of the regression analysis and the subsequent robustness checks; Sect. 5 concludes.

2 Literature review

2.1 The composite link between technological change and employment: a compact overview

The complex and multifaceted nexus between technological progress and employment has long been studied and debated. The dominant theoretical framework identifies a direct effect of innovation on employment, which is mainly positive for product innovation and mainly negative for process innovation. However, this direct impact often intertwines with various indirect effects, emerging at different levels of aggregation, which may amplify or counterbalance the direct effect of innovation, making predictions about the final outcome particularly challenging (Arenas Díaz et al., 2024; Calvino & Virgillito, 2018; Vivarelli, 2014).[3]

In the last two decades, also thanks to increasing data availability—especially at the firm-level (Arenas Díaz et al., 2024)—, a burgeoning literature has empirically analysed the puzzling innovation-employment link. From this broad literature, which was scrutinized and reviewed by various extensive surveys (e.g., Autor, 2022; Calvino & Virgillito, 2018; Mondolo, 2022; Montobbio et al., 2024), including some meta-analytic reviews (e.g., Arenas Díaz et al., 2024; Ugur et al., 2018), it emerges that the sign and the direction of the relationship under scrutiny are significantly affected by both the selected type of technology and the level of aggregation (e.g., country/macro, sector, firm). Focusing on firm-level analyses (e.g., Barbieri et al., 2020a; Dixon et al., 2021; Pellegrino et al., 2019), the available empirical research suggests that, on the one hand, disembodied technological change, often measured by

[3] One of the most popular theories that capture the direct and indirect effects of innovation on employment is the "Compensation theory" or "Compensation framework", which dates back to Karl Marx but which, during the twentieth century and the first decade of the twenty-first century, has been extended and elaborated by various schools of thought. To sum up, the main mechanisms of compensation/job creation which are triggered by technological change are: (1) New Machines; (2) Decrease in prices; (3) Decrease in wages; (4) New Investments; (5) Increase in incomes; (6) New products. For a more detailed discussion, see Vivarelli (2014), Barbieri et al. (2020b), and in particular the survey by Calvino & Virgillito (2018), who also illustrate the challenges related to these mechanisms and the attempts made by some empirical studies to account for them.

R&D expenditures and mainly related to product innovation, tends to complement, rather than substitute, human workers, especially in larger and innovative companies operating in dynamic or high-tech sectors; on the other hand, embodied technological change, captured by investments in new physical capital and mostly associated with process innovation, typically encompasses a labour-saving component too. Furthermore, heterogeneity also exists within the broad bundle of embodied technologies. Specifically, I4.0 technologies that are mainly software-based are expected to be more labour-friendly than machine-based technologies, sometimes referred to as automation technologies, such as industrial robots and additive manufacturing (Balsmeier & Woerter, 2019). Additionally, some studies demonstrate that firms adopting new digital technologies ("adopters") often surpass non-adopters not only in terms of economic performance, but also of employment outcomes, thus stressing the importance of catching up with the ongoing digital transformation in order to strive or even survive (e.g., Aghion et al., 2020; Acemoglu et al., 2020; Dosi & Mohnen, 2019; Koch et al., 2021;).

Importantly, technological change can affect not only labour quantity, but labour composition as well (Calvino & Virgillito, 2018) as stressed by the Skill-Biased Technological Change (SBTC) hypothesis. The basic idea underlying this theory, which was conceptualized by Acemoglu and Autor (2011) in the so-called canonical model, is that Information and Communication Technologies (ICTs) are "skill-biased": they increase the relative productivity of high-skilled workers, who are typically more able to use new technologies, and consequently boost the relative labor demand of such workers compared to low-skilled workers (Katz & Murphy, 1992). Accordingly, this theory suggests that technologies tend to complement high-skilled/educated employees and replace the low-skilled/low-educated workforce.

The SBTC hypothesis has been proved empirically suitable in accounting for the trend in the skill premia and employment experienced by the United States and other OECD countries, especially during the seventies and the eighties (e.g., Acemoglu & Autor, 2011; Goldin & Katz, 2008; Katz & Murphy, 1992; Piva & Vivarelli, 2002). However, it presents various limitations (see Mondolo, 2022, for an overview); notably, since the seminal contribution by Autor et al. (2003), who proposed a "nuanced version" of the SBTC hypothesis known as the Routine-Biased Technological Change (RBTC) hypothesis, several studies have investigated the complementarity/substitutability between technologies and human tasks.[4] All in all, from this extensive literature centred on the "qualitative" effect of technological progress on labour, it emerges that technological change tends to complement high-skilled workers mostly performing non-routine tasks, generally to the detriment of low or middle-skilled workers mostly carrying out routine tasks (see Montobbio et al., 2024, and Deming & Silliman, 2024, for a recent review).

It should be noted that the RBTC hypothesis too presents some limitations (see Biagi & Sebastian, 2018), especially if applied to new digital technologies: the latter, compared to older technologies mostly related to the third/ICT industrial revolution,

[4] Acemoglu & Autor (2011, p. 1045), who refine Autor, Levy and Murnane's framework, define a task as a "unit of work activity that produces output (good and services)", whereas a skill is a "worker's endowment of capabilities for performing various tasks".

exhibit a pronounced derivative nature and pervasive influence and, by triggering transformations in organisational forms, business architecture, and business models, can impact the entire production chain and strategic layout (Gaglio et al., 2022; Huang, 2024; Vial, 2019). Accordingly, in recent years, part of the research on technological progress and employment in the context of the I4.0 paradigm has shifted its attention from tasks (back to) skills, thus fueling a more nuanced and modern version of the SBTC framework. In particular, scholars have recently attempted to identify the skills most required for the ongoing digital transformation, and sometimes the underlying mechanisms of provision as well (see Sect. 2.2).

2.2 An empirical assessment of Industry 4.0 skill requirements

2.2.1 Industry 4.0 and skill provision: evidence from case studies

As previously mentioned, to harness the potential and address the challenges stemming from the Fourth Industrial Revolution, a growing body of literature has recently explored the skill demand fostered by the so-called Industry 4.0 paradigm. Specifically, various case studies, generally based on interviews with managers and employees of the firm(s) under scrutiny, shed light on workers' perceptions of the impact of digitalization on jobs and the competencies they regard as most relevant for successfully navigating the ongoing digital transformation.

One of the most comprehensive qualitative analyses on this issue has been carried out by Cimini et al. (2021): the authors, who draw upon the "socio-technical model" (Trist & Emery, 2005), perform a multiple case study of Italian small and medium enterprises (SMEs) in manufacturing in which they consider four types of skills/competencies based on the classification ofHecklau et al. (2016).[5] From this work, it emerges that the increasing adoption of I4.0 technologies prompts companies to require both technical and non-technical skills (although the need to introduce or strengthen non-technical skills often arises later, compared to the need for new technical skills). This study also highlights the importance of training for acquiring or strengthening the required competencies.

Evidence of complementarity between technical skills and non-technical skills spurred by digitalisation is also reported in the qualitative analyses by Achtenhagen & Achtenhagen, 2018 (who look at some German companies in the food industry and focus on the role of training), Kannan & Garad, 2021 (who, like Cimini et al., draw on Hecklau and co-authors' framework to explore skill needs in an electronics manufacturer located in Southern Malaysia) and Colombari et al., 2024 (who, building upon the socio-technical approach, conduct 34 semi-structured interviews both in the Italian and Spanish automotive sector). Additionally, some case studies (e.g., de Assis Dornelles et al., 2023; Szalavetz, 2022) shed light also on the risk of job dis-

[5] The four identified skill types are: namely: technical (referring to state-of-the-art knowledge, increasingly related to IT, automation programming and data analysis), methodological (i.e., skills and abilities used to handle situations and problems, such as conflict solving, creativity and decision-making), personal (i.e., values, motivations and individual attitudes, including flexibility, a motivation to learn and the ability to work under pressure) and interpersonal (i.e., social skills and abilities to communicate and cooperate with others, such as networking skills, leadership skills and the ability to work in a team).

placement and deskilling, which may prevail, at least for some workers, if a company strongly relies on automation aimed at cost minimization and if appropriate managerial interventions envisaging labour upgrading are not implemented.

All in all, from this body of literature, it emerges that the ongoing digital transformation is propelling the demand for various skills, including non-technical skills, which, as illustrated by Deming (2017), have become more and more valuable starting from the beginning of the twenty-first century. These skills, in turn, can foster processes of labour upgrading. However, especially in some companies and sectors, and in the absence of proper labour upgrading plans, new digital technologies may also exert displacement or deskilling effects on some workers.

2.2.2 A quantitative assessment of I4.0 skill requirements and the mechanisms of skill provision

In recent years, various studies have quantitatively assessed how the adoption of I4.0 technologies drives skill needs and the channels underpinning skill provision, which can occur either through hiring of new workers possessing adequate expertise and/or (external or on-the-job) training of the existing workers.

Some of these contributions focus on the effect of digitalization on training. Specifically, Pedota et al. (2023), leveraging survey data on a large sample of Italian firms, show that I4.0 technologies are positively associated with ICT upskilling for both ICT and non-ICT employees carried out through any form of internal or external ICT-related training. Also, Jiang et al. (2024) show that the introduction of the point-of-sale (POS) technology significantly increased a firm's likelihood of (on-the-job) training in a sample of almost 2500 Chinese companies. Focusing on various types of training content, they also report that POS adoption is associated not only with the demand for the essential skills needed to run the POS system, but also with marketing, communication, and customer service skills.

Despite its valuable contribution, we may wonder to what extent Jiang and co-authors' findings, which are based on a quite specific type of technology/system, still hold when we consider other technologies and/or a broader technology array. A study that looks at various types of digital technologies is the one by Gathmann et al. (2024). In their comprehensive study on digital technology adoption spurred by the Covid-19 pandemic conducted on 2000 German establishments, the authors also look at the effect of overall digital technology adoption on firm-sponsored training, and in particular on the need of training aimed at enhancing six different types of skills which include both technical ("hard") skills (e.g., IT skills) and non-technical ("soft") skills (e.g., skills for online management and planning skills). The empirical analysis reveals that, in the aftermath of the Covid-19 pandemic, firms investing in digital technologies have reported a substantially higher need for training in all six competencies, among which online communication and cooperation skills stand out. However, this result may be partly driven by the selected array of digital technologies (which primarily consist of software-based technologies, including software for collaboration on and administration of shared documents and software for digital communication and process automation) and the focus on the post-pandemic period (i.e., year 2021), during which we assisted to a sharp increase in online communication and cooperation.

Different results are obtained by Brunello et al. (2023), who find that the adoption of advanced digital technologies is associated with a decline in training. The authors suggest that the substitution effect of digital technologies is concentrated in jobs and skills that typically require formal training; conversely, the productivity effect could be more intense in jobs requiring skills that can be found only in the external labour market, through hiring, or demanding skills that can be developed through an informal learning process. Despite that, the authors leave open the question about which of the two alternative explanations actually prevails.

While the four aforementioned studies focus on training, Huang, (2024) assess the effect of digitalization on employment. From their quantitative analysis of a large sample of Chinese A-share manufacturing companies, it emerges that firms' digital transformation (measured through text-mining techniques applied to corporate annual reports) simultaneously increases the demand for both technical and non-technical workers, with the former experiencing a larger effect. Hence, in this study, workers' skills are indirectly captured by the prevaling task content of their job position, according to which employees are classified as either technical or non-technical.

The results of Huang, (2024) are complemented by those of Li et al. (2024), who, using an unbalanced panel of Chinese listed companies, explore the effect of digitalization (measured using text analysis techniques as well) on "labour upgrading". The latter is proxied by employment outcomes in which employees are classified based on the technical nature of their job (i.e., technical or nontechnical employees), the level of formal education (i.e., employees possessing or not at least a bachelor's degree) and the production content of the job (i.e., production vs non-production workers). The authors find that digitalized firms have a greater demand for highly technologically skilled and highly educated employees; they also show that digitalization favours training, which, in their opinion, may alleviate the labour shortage stemming from the costs and time required for labour adjustments.

One of the most comprehensive analyses of the effects of I4.0 technologies on both hiring and training is the recent study by Cirillo et al. (2024), which uses a large sample of Italian firms and combines firm-level data with worker-level information. The rich empirical analysis reveals that the adoption of I4.0 technologies (i.e., Internet of Things, robotics, Big Data Analytics, Augmented Reality and cybersecurity) is associated with an increase in the firm-level hiring rate (especially for young workers and for workers with high education levels), a reduction in separation rate and an increase in workplace training. Accordingly, this contribution provides a solid, fine-grained account of the effect of digital transformation on labour outcomes, but does not disentangle the skill types incorporated in the identified labour market flows.

A study that focuses on the impact of advanced technologies on skills, and in particular on the potential ability of technological change to displace skills, is the one conducted by McGuinness et al. (2021). Drawing on the European Skills and Jobs Survey, the authors develop a unique measure of what they define as "skill-displacing technological change" and empirically show that, contrary to popular belief, it is not associated with deskilling but, on the contrary, with dynamic worker upskilling.

Finally, it is worth recalling the study by Shakina et al. (2021), who, using a panel VAR approach, show that the relationship between I4.0 technologies and digital skills is bilateral: previously acquired skills foster technology adoption, which, in turn, demands new skills and affects labour composition and quality. This result stresses the importance of addressing endogeneity issues to limit the risk of biased results in the assessment of the composite relationship between technology adoption and skills.

2.3 Research hypotheses

From the literature reviewed in Sect. 2.2, it emerges that the adoption of I4.0 technologies spurs not only the demand for technical skills, but also for those horizontal and soft skills, i.e., "business skills", that can help companies strengthen their "technological readiness" and reap the strategic benefits of the digital transformation. This result aligns with Prifti and co-authors' assertion that the I4.0 transformation will require employees to possess a wide range of competencies (Prifti et al., 2017). Also, this finding supports the idea that skills are never applied in isolation, but within bundles. Such complementarity among different skills produces synergies that, in turn, increase their economic value (see the interesting empirical analyses by Paklina & Shakina, 2022, and Stephany & Teutloff, 2024). In light of these considerations, we expect our empirical analysis to confirm that the adoption of I4.0 technologies is positively associated not only with the introduction of new technical skills, but also with the integration of additional business skills. Accordingly, we put forward this preliminary research hypothesis, labelled "hypothesis zero" (H0):

H0. *The adoption of digital technologies is positively associated with the acquisition of both new technical skills and business skills.*

A more heterogeneous picture may emerge if we split the firm's overall bundle of digital technologies into different technology categories. Although they share some peculiarities, I4.0 technologies are indeed quite heterogeneous in terms, for instance, of the degree of technical complexity, the percentage of software and hardware components, and the central business areas and functions in which they are implemented. In particular, software-based technologies (e.g., ERP, CRM, management software) often underpin managerial systems and platforms used to sell and advertise products and services, and enable online communication and collaboration with customers and among employees, especially after the outbreak of Covid-19 (Franco & Pietrovito, 2024). Hence, their adoption is expected to stimulate the demand for both technical and business skills. Conversely, machine-based and hybrid technologies (e.g., robots, additive manufacturing, IoT) are generally regarded as production technologies and typically require specific technical skills. Nevertheless, machine-based technologies encompass the introduction of labour-saving automated production processes and may therefore not generate any additional skill requirements (Acemoglu & Restrepo, 2019). Hybrid technologies, on the other hand, may entail a more intense reinstatement effect due to the underlying human–machine interaction. In light of these considerations, we expect heterogeneous skill requirements across different types of digital technologies, and formulate the following research hypothesis (H1):

H1a *The adoption of digital technologies, driven by hybrid technologies, is positively associated with the acquisition of new technical skills;*

H1b *The adoption of digital technologies, driven by software technologies, is positively associated with the acquisition of new business skills.*

Another relevant issue that we address in this work concerns the mechanisms underlying skill acquisition. New skills can be obtained either on the internal labour market, by updating and improving the competencies of the current workers through training, or on the external labour market, by hiring new workers. However, based on the existing literature, it is difficult to predict whether and to what extent these skill requirements will be met through training current workers and/or recruitment. On the one hand, the adoption of I4.0 technologies, which often encompass an automation component, may lead to the displacement of existing jobs and skills while stimulating the demand for those skills that can be sourced in the external labour market through hiring (Feng & Graetz, 2020),[6] with a consequent shift in the skill formation process from training to hiring; this would imply the existence of a technology bias that encourages hiring to the detriment of training. On the other hand, as suggested by Goldin and Katz (2008) in their seminal study on the "race between education and technology", the evolution of the skill-technology complementarity in a digital paradigm might lead to the replacement of education with training, with the latter being the skill formation process that better supports investments in new technologies (Jona-Lasinio & Venturini, 2024).

A possible solution to this dilemma is offered by Becker's (1962) distinction between general ("transferable") and specific ("non-transferable") skills: as general skills can enhance a productivity gain in all firms (or at least in those belonging to the same industry), thus reducing firms' incentive to train their workers, they should be provided by the education system. Conversely, specific skills can hardly be transferred from one company to another; hence, firms capture almost all the benefits from subsequent improvements in labour productivity and are thus motivated to invest in training.

Another, more managerial skill taxonomy which partly overlaps with Becker's classification is the one proposed by Nordhaug (1998): the author identifies six categories of competencies, including meta-competencies and technical trade competencies; specifically, meta-competencies include "(…) the ability to communicate and to cooperate with others, general negotiation skills, and ability to adjust to change" (Nordhaug, 1998, p. 12), and can be related to Becker's general skills. Technical trade competencies, instead, refer to interventions aimed at the execution of specific tasks common to a given technology. Being task-specific, these competencies can be developed quickly, but can also display a growing degree of obsolescence over time. In his analysis of the Italian labour market, Pedrini (2020) shows that technical trade skills are mostly developed through training, while meta-competencies are limitedly acquired through training interventions.

[6] The underlying theoretical assumption is that it is easier to automate tasks that require training than tasks that require little or no training.

Becker's general skills and Nordhaug's meta-competencies significantly overlap with our notion of business skills, while specific skills and technical trade competencies are encompassed in our definition of technical skills. In line with these taxonomies, the development of new technical skills, which are firm-specific and hardly transferable across organisations, should be at least partly grounded in training interventions. On the contrary, business skills are easily portable from one employer to another; as a result, we expect that their development does not necessarily require training interventions, but can mainly be achieved by resorting to the external labour market.

Given these considerations, we extend Hypothesis 1 through the following additional hypothesis (Hypothesis 2—H2):

-H2a. *The demand for technical skills is mainly driven by hybrid technologies and is mostly satisfied through training;*

-H2b. *The demand for business skills is mainly driven by software technologies and is mostly satisfied through hiring.*

3 Empirical strategy

3.1 Data

The primary data source for our empirical analysis is a unique survey originally designed in early 2019 to collect original information on relevant business activities, such as investment policy, technological innovation, changes in the business model, position in the value chain, and relationships with clients and suppliers. The survey was administered for the first time, to a representative sample of Italian firms, during the months preceding the outbreak of the Covid-19 pandemic, as well as about three years later, through a second wave. The processes of sample selection and answers' collection and elaboration are summarised below.

First, we identified about 369,000 companies with less than 1000 employees in 2019 from the AIDA-BvD database.[7] Then, we randomly selected about 15% of these firms (55,124 units), resulting in a representative sample stratified by industry, firm size, and region. The survey was conducted between October 2019 and February 2020, involving telephone calls and e-mail communications. 16,492 companies completed the questionnaire, yielding a response rate of 27.5%. We discarded companies that provided significantly incomplete responses, and matched the usable information with balance-sheet data (e.g., revenues, ROA, year of incorporation, etc.) retrieved from the commercial database AIDA-Bureau van Dijk (BvD). In doing so, we ended up with a sample of 4,214 firms for which both survey data and financial information were available. A more detailed description of the procedure for sample selection and

[7] We excluded very large firms as they are likely to differ in terms of investment decisions, including investments in digital technologies, from SMEs, which represent the large majority of Italian companies.

data collection for the first wave and a compact assessment of sample representativeness are contained in Section A1 and Section A2 of Appendix 1, respectively.

The second wave of the survey was designed in Spring 2022 to investigate how the pandemic had influenced firms' behaviour in a set of strategic activities. The related questionnaire covered the same topics as the first wave and included a few additional questions, including some aimed at further delving into the adoption of some I4.0 technologies. On September 20th, 2022, the questionnaire was sent via e-mail to the companies (about 4,200) that, when they filled in the first version, declared they would let us contact them in the future if we needed further information. As we obtained about 1000 answers, the response rate of the second wave was close to 24%. The collection of information from the second survey was completed in December 2022. After performing some data cleaning, integrating financial information from AIDA for the last available years (2022 and 2023), and merging the second-wave survey data with information from the first wave, we ended up with a dataset comprising 934 firms with all relevant information available for both 2019 and 2022.

As far as digital technologies are concerned, both waves include questions about the adoption of the following technologies: IoT, Big Data Analytics, interconnected production cells, industrial robots, additive manufacturing, augmented reality and wearables, management software (such as ERP and CRM), cloud computing, and cybersecurity. In the survey, we also asked firms whether, during the previous three years, they had required new skills falling within two relevant macro-categories, namely, technical skills and business skills. Drawing upon the well-known O*NET taxonomy (see Allen et al., 2012), we identify technical skills as those typical abilities that are required to accomplish production tasks, and include, for instance, equipment installation and programming. With the term business skills, we instead refer to a more heterogeneous category of cross-functional competencies typically required to effectively run a company, including financial and material resource management and social skills that enhance interactions with colleagues and customers. Further details on the identification of the two skill families and the list of survey questions used in this study are reported in Section A3 of Appendix 1.

Finally, drawing upon the Italian National Institute of Statistics (ISTAT)'s "Survey on the diffusion of ICT in the Italian firms", we integrated data (available for both 2014 and 2019) on the share of online sales in the NUTS-3 region in which a company is located. This variable is used to instrument the key regressor of the main regression analysis in the IV regression, as discussed in Sect. 4.2.2.

3.2 Econometric strategy and variables

We begin our empirical analysis by estimating the probability function of companies demanding either technical or business skills by carrying out the following probit regressions:

$$P\left(Technical\_Skills_{i,2022}=1|\boldsymbol{X}_{i,t}\right)=\Phi\left[\beta_0+\beta_1 DigitalTech_i+\boldsymbol{\beta}_2\left(\boldsymbol{Contr}\right)_{i,2019}+\eta_r+\sigma_s\right] \quad (1)$$

$$P\left(Business\_Skills_{i,2022}=1|\boldsymbol{X}_{i,t}\right)=\Phi\left[\beta_0+\beta_1 DigitalTech_i+\boldsymbol{\beta}_2\left(\boldsymbol{Contr}\right)_{i,2019}+\eta_r+\sigma_s\right], \quad (2)$$

where the two dependent variables, *Technical_Skills* and *Business_skills*, are dichotomous variables capturing the acquisition (during the three previous years) of new technical skills and business skills, respectively, *DigitalTech* is the key regressor, *Contr* is a vector of firm-level controls, η captures regional (Nuts-1) fixed-effects and σ captures industry fixed effects.[8] *DigitalTech* initially consists of a dummy variable (DigitalTech_d) indicating whether a company had fully adopted at least one type of digital technology by 2019. We also replace this regressor with *DigitalTech_count* (a count variable indicating the number of I4.0 technologies simultaneously adopted by a company, ranging from zero to eight) to assess the cumulative role of new digital technologies in determining firms' skill requirements. After that, to explore differences in skill requirements across software, hybrid, and machine-based technologies, we use, separately and then jointly, the dummies *Software_Tech*, *Hybrid_Tech*, and *Machine_Tech* as key regressor(s). The set of covariates also includes a number of control variables referring to firm-level characteristics that are likely to influence companies' propensity to adopt I4.0 technologies; specifically, we control for firm age (*Age_firm*), family management and/or ownership (*Family_firm*), average labour productivity (*Labour_product*), turnover (*Turnover*), revenues (*Revenues*), profitability (*ROA*) and a dummy indicating whether the firm has introduced new corporate functions (*New_Functions*).

We also look at how digital technologies are associated with different skill types sourced from either the internal or external market. To this end, we re-estimate Eqs. [1] and [2] after decomposing both *Technical_Skills* and *Business_Skills* into their training and hiring components; specifically, we run a new set of probit regressions in which we use, as dependent variable, *Technical_Training, Technical_Hiring, Business_Training* and *Business_Hiring*, respectively:

$$P\left(Technical\_Training_{i,2022}=1|\boldsymbol{X}_{i,t}\right)=\Phi\left[\beta_0+\beta_1 DigiralTech_i+\boldsymbol{\beta}_2\left(\boldsymbol{Contr}\right)_{i,2019}+\eta_r+\sigma_s\right] \quad (3)$$

[8] To provide a sufficiently fine-grained level of industry fixed effects while mitigating sample reduction –which can arise when overly granular industry classifications are used – we rely on the "section" level of the NACE classification of economic activities, as adopted in the Italian ATECO 2007 system. Each of the 38 sections aggregates between one and three consecutive NACE two-digit sectors. For example, the "Manufacturing" section, which contains 13 sections, includes: CA: Manufacture of food, beverages, and tobacco, which comprises NACE sectors 10 to 12; CB: Manufacture of textiles, clothing, leather and accessories (13 to 15); CC: Manufacture of wood, paper and printing (16 to 18); CD: Manufacture of coke and refined petroleum products (19); CE: Manufacture of chemical substances and products (21); CF: Manufacture of pharmaceutical, medicinal-chemical and botanical articles 21 9 CG Manufacture of rubber and plastic products, other non-metallic mineral products 22+23; CH: Manufacture of basic metals and fabrication of fabricated metal products, except machinery and equipment (24 and 25); CI: Manufacture of computers, electronic and optical equipment (26); CJ Manufacture of electrical equipment (27); CK: Manufacture of machinery and apparatus n.e.c. (28); CL: Manufacture of transport equipment (29 and 30); CM: Other manufacturing, repair and installation of machinery and equipment (31 to 33).

$$P\left(Technical\_Hiring_{i,2022}=1|\boldsymbol{X}_{i,t}\right)=\Phi\left[\beta_0+\beta_1 DigiralTech_i+\boldsymbol{\beta}_2\left(\boldsymbol{Contr}\right)_{i,2019}+\eta_r+\sigma_s\right] \tag{4}$$

$$P\left(Business\_Training_{i,2022}=1|\boldsymbol{X}_{i,t}\right)=\Phi\left[\beta_0+\beta_1 DigiralTech_i+\boldsymbol{\beta}_2\left(\boldsymbol{Contr}\right)_{i,2019}+\eta_r+\sigma_s\right] \tag{5}$$

$$P\left(Business\_Hiring_{i,2022}=1|\boldsymbol{X}_{i,t}\right)=\Phi\left[\beta_0+\beta_1 DigiralTech_i+\boldsymbol{\beta}_2\left(\boldsymbol{Contr}\right)_{i,2019}+\eta_r+\sigma_s\right] \tag{6}$$

Technical_Training is a dichotomous variable measuring whether a company has acquired new technical skills through training, while *Technical_Hiring* is a dummy variable that tells us whether a company has integrated new technical skills through hiring. Conversely, *Business_Training* is a dummy capturing whether a firm has introduced new business skills through training, and *Business_Hiring* is a dummy reporting whether a company has sourced new business skills through training. In all estimates, we cluster the standard errors at the industrial (NACE 2-digit) level and account for potential collinearity among the explanatory variables by calculating the variance inflation factor (VIF).

3.3 Descriptive statistics

In this section, we provide a preliminary descriptive account of our variables of interest. Table 1 reports baseline descriptive statistics for all variables in the regression specifications reported in Sect. 4.1, along with a concise definition and the corresponding data source. Focusing first on the two main dependent variables (i.e., *Technical_Skills* and *Business_Skills*), we observe that, in 2022, 27% of the sampled companies had sourced new technical competencies during the past three years; hence, the demand for such skills is relatively widespread; conversely, the acquisition of new business skills is limited to 12% of the firms under scrutiny. Interestingly, heterogeneity across these two main skill categories emerges when we decompose them into their training and hiring components. Specifically, according to the average values of the dependent variables *Technical_Training, Technical_Hiring, Business_Training* and *Business_Hiring*, technical skills are mainly acquired through training (22.9% vs 4.1%), while business skills are usually sourced in the external labour market through hiring (11.5% vs 3.7%).

Concerning the variables measuring the adoption of I4.0 technologies, we observe that the majority of the selected firms (74%) had introduced at least one new digital technology by the end of 2019 (as captured by the dummy variable *DigitalTech_d*); however, the average number of adopted technologies is relatively low (*DigitalTech_count.* displays an average value of 1.7 compared to a maximum value of 7). If we look at the three categories in which our digital technologies are grouped, i.e., *Software_Tech*, *Hybrid_Tech* and *Machine_Tech*, we observe that the adoption of software technologies (reported by 72.4% of the sampled companies) is much more widespread than the adoption of hybrid and (I4.0) machine-based technologies (amounting to 12.2% and 8.9%, respectively). Finally, looking at the average values of the variables *Employees* and *Family_firm,* we notice that the majority of

Table 1 Variable definitions and baseline descriptive statistics

Variable	Definition	Source	Obs	Mean	Std. Dev	Min	Max
Technical_Skills	Whether the firm has introduced new technical skills before 2022	Our survey	934	0.27	0.444	0	1
Technical_Training	Whether the firm has introduced new technical skills through training before 2022	Our survey	934	0.229	0.42	0	1
Technical Hiring	Whether the firm has introduced new technical skills through hiring before 2022	Our survey	934	0.041	0.198	0	1
Business Skills	Whether the firm has introduced new business skills before 2022	Our survey	934	0.12	0.325	0	1
Business_Training	Whether the firm has introduced new business skills through training before 2022	Our survey	934	0.037	0.19	0	1
Business_Hiring	Whether the firm has introduced new business skills through hiring before 2022	Our survey	934	0.115	0.319	0	1
DigitalTech d	Whether the firm has adopted at least one new digital technology (of any type) by 2019	Our survey	934	0.741	0.438	0	1
DigitalTech count	Number of new digital technologies adopted by the firm by 2019	Our survey	934	1.689	1.469	0	7
Software tech.	Whether the firm has adopted at least one software technology by 2019	Our survey	934	0.724	0.447	0	1
Hybrid_Tech	Whether the firm has adopted at least one hybrid technology by 2019	Our survey	934	0.0122	0.328	0	1
Machine_Tech	Whether the firm has adopted at least one machine-based technology by 2020	Our survey	934	0.089	0.285	0	1
Employees	Number of employees in 2019	Aida-BvD	924	23.036	84.382	1	2086
ROA	return on assets (ROA) in 2019	Aida-BvD	934	7.641	12.926	- 87.59	86.94

Table 1 (continued)

Variable	Definition	Source	Obs	Mean	Std. Dev	Min	Max
Revenues	Revenues (in euro)	Aida-BvD	934	4930	18,191.3	1	3E+05
Family firm	Whether a firm is a family business	Our survey	934	0.864	0.343	0	1
New_Functions	Whether a firm has added new corporate functions by 2019	Our survey	934	0.319	0.467	0	1
Age	Firm age in 2019	Aida-BvD	934	20.14	14.8	1	119
Labour_product	Labour productivity in 2019	Aida-BvD	924	61.23	68.114	-221.11	1201

Table 2 Acquisition of new skills by adopters and non-adopters of I4.0 technologies (mean comparison)

	Digital tech (any)	Software tech.	Hybrid tech.	Machine tech
Panel a (Technical Skills)				
0	0.698	0.677	0.091	0.085
1	0.857	0.849	0.206	0.099
Diff. (t-test)	0.159*	0.172*	0.115*	0.014*
Panel b (Business Skills)				
0	0.727	0.708	0.113	0.086
1	0.839	0.839	0.188	0.107

t-test significant at the 5% level (*); with the term "adopters", we refer to companies that, by 2019, had already fully adopted at least one type of any digital technology (column 1), software technology (column 2), hybrid technology (column 3) and machine-based technology (column 4)

our sample consists of SMEs and family businesses, thus exhibiting two well-known features of the Italian economy.

Table 2 provides a more detailed picture of our sample by comparing adopters and non-adopters of I4.0 technologies in terms of their propensity to acquire new technical skills (panel a) and new business skills (panel b). We observe that, on average, adopters of new digital technologies (whether or not we distinguish across technological categories) exhibit a higher propensity to source both technical and business skills, with the null hypothesis of non-significant differences in means always rejected. All in all, these insights are consistent with the correlation analysis reported in Table 14 of Appendix 2.

A more straightforward comparison across categories of technologies and skills emerges from Fig. 1, which illustrates the adoption rates of (any type of) I4.0/digital technologies and the share of firms that have introduced new technical and business skills. As previously mentioned, the dominant technological category is software, while the most required new competencies are technical skills.

Finally, Fig. 2 explores between-industry heterogeneity in the adoption of (any) digital technologies. The highest adoption rate (i.e., 100%, indicating that all sampled firms operating in the sector had adopted at least one new digital technology by 2019) is observed in Pharmaceutical, Telecommunications, Arts & Entertainment and the

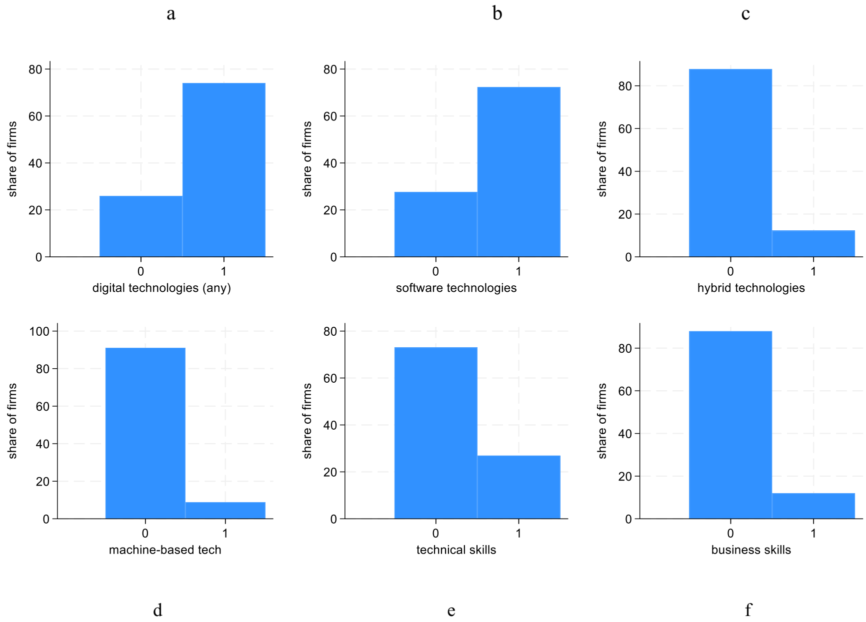

Fig. 1 Adoption of digital technologies and skill requirements across the sample of 934 companies. Source: authors' elaboration of data from the survey. Note: the figure displays the share (in % terms) of firms that have adopted (value = 1) or not adopted (value = 0) any type of digital technologies, software technologies, hybrid technologies and machine-based technologies by 2019 (panels **a**, **b**, **c** and **d** of Fig. 1, respectively), as well as the share of firms that have introduced (or not introduced) new technical skills and new business skills before 2022 (panels **e** and f of fig, respectively)

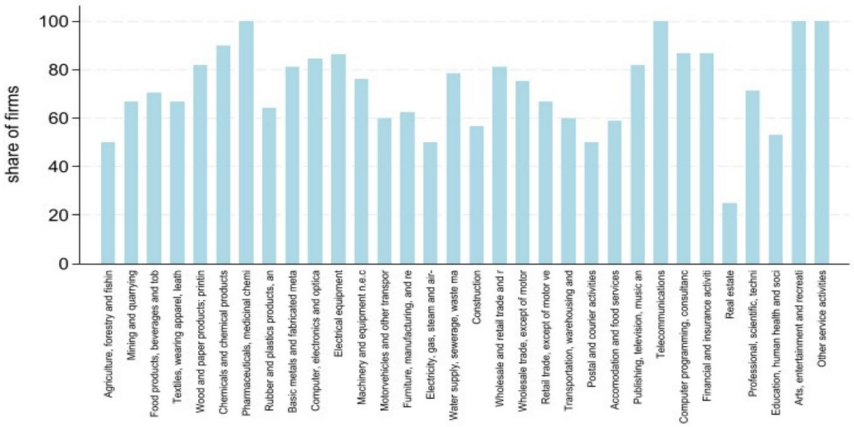

Fig. 2 Adoption of digital technologies by Nace-2 sector across the sample of 934 companies. Source: authors' elaboration of data from the survey. The sectoral (Nace 2-digit) codes are retrieved from Aida-Bvd. Note: this figure shows the % share of companies that have fully adopted at least one new digital technology by 2019 in each Nace-2 digit sector covered in the sample

residual category “Other service activities”, whereas the lowest average adoption rate is found in firms operating in the real estate business.

Three additional figures (Figs. 4, 5, 6) that further explore heterogeneity across industries, technology types and skill types, respectively, are included in Appendix 2.

4 Results of the regression analysis

4.1 Main results

In this section, we present and discuss the findings of the core part of our empirical analysis, through which we investigate how and to what extent the adoption of I4.0/ new digital technologies spurs companies’ acquisition of new skills. In doing so, we also explore heterogeneity across technologies, skill types, and skill-provision channels.

Table 3 reports the results of the probit regressions examining the relationship between the adoption of new digital technologies and demand for technical and business skills. First, in line with our preliminary hypothesis “zero” (H0), we see that companies that, by the end of 2019, had completed the adoption of at least one type of new digital technology exhibit, on average, a higher probability of introducing both new technical skills and new business skills in the subsequent years. Also, as expected, the economic magnitude and statistical significance of the coefficient of the key regressor are higher when the dependent variable is *Technical Skills*. Specifically, the adoption of at least one category of I4.0 technology is associated with a 13.7 p.p. increase in firms’ propensity to acquire new technical competencies (column 1), while such an increase amounts to only 6.4 p.p. in the case of business skills (column 7). We further delve into the relationship between technical and business skills by estimating a bivariate probit model (see Sect. 4.2.1).

Similar results are obtained when we replace the dummy capturing technology adoption with the count variable *DigitalTech_count*. As expected, a larger array of new digital technologies, which generally implies greater technical complexity but can also require more effort in managing business-related aspects, is associated with a higher probability of acquiring both technical skills and, to a lesser extent, business skills.

In the rest of the analysis, we focus on the dummy variable capturing the adoption of (any type of) digital technologies and, in particular, on its three main components, namely, software, hybrid and machine-based technologies. In this respect, both software and hybrid technologies seem to stimulate the demand for technical competencies and (to a lesser extent) business skills (columns 3–6 and 9–12 of Table 3). We also notice that the gap between the two skill types is greater in the case of hybrid technologies, which often involve considerable technical complexity and/or relevant human–machine interaction. The strengthening of business competencies, instead, is mainly associated with software technologies: the latter can lead to new ways to communicate with potential and current customers, coordinate with other workers, etc., thus spurring the acquisition of related business skills. All in all, these findings provide empirical support for Hypothesis 1. Finally, we observe that the coefficient of the dummy variable capturing the adoption of machine-based technologies is never statistically significant; this may be due to the labour-saving component of these technologies, which offsets the positive reinstatement effect on tasks and skills.

Looking at the set of control variables, we notice that, as expected, larger and more profitable firms are more likely to require new skills (although the coefficient of ROA is never significant with business skills). At the same time, older companies, which may be more risk-averse and less digitalized, tend to reduce their investments in new technical competencies. Labour productivity does not seem to be a significant predictor of companies' probability of subsequently acquiring new skills; the weak negative association between labour productivity and business skills may be attributable to the fact that companies that already possess high levels of labour productivity have a lower need to further enhance their bundle of business competencies. Finally, family firms do not significantly differ from corporations in their propensity to acquire new skills.

After providing a general overview of I4.0-driven skill requirements, we conduct a more fine-grained analysis in which, for both the skill types under scrutiny, we shed light on the two mechanisms of skill acquisition, namely, training and hiring. Looking at Table 4, which disentangles the skill acquisition process into training and hiring aimed at enhancing the workforce's technical expertise, we see that the overall adoption of new digital technologies is positively associated with both training (column 1) and hiring (column 6). When we split overall technology adoption into its three main components (columns from 2 to 5 and from 7 to 10), we notice that software technologies are positively related to both hiring and (especially) training. This propensity to implement training to improve their skill bundle is more pronounced in the case of hybrid technologies, as posited by Hypothesis 2a. Finally, consistent with previous estimates, the dummy variable for machine-based technologies is not significant.

In the same vein, we assess the channels through which business skills are provided. From Table 5, it emerges that the overall adoption of digital technologies is not a predictor of firms' propensity to training, while it is associated with a slight increase in hiring (columns 1 and 6). These ambiguous results may hide significant between-technology heterogeneity. In this respect, we observe that software technologies are positively associated with hiring practices. This result supports hypothesis 2b; notably, it confirms that business skills are more readily available in the external labour market, whereas their internal development through training may entail the risk of subsequent poaching by competitors due to the high transferability of this skill type. We also find that hybrid technologies are instead positively related to training. This additional finding may be ascribable to the fact that firms adopting such technologies may need some prior idiosyncratic knowledge of their production process to accomplish managerial and relational tasks.

All in all, this more fine-grained analysis of skill requirements, which focuses on the sources of skill provision, further highlights significant between-technology heterogeneity, underscoring the importance of examining different technology bundles. A summary of the main results concerning the relationship between technological macro categories, skill types and skill provision mechanisms is provided in Table 6.

Table 3 Adoption of new digital technologies and skill demand (average marginal effects of probit estimates)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	Technical Skills	Technical Skills	Technical Skills	Technical Skills	Technical Skills	Technical Skills	Business Skills	Business Skills	Business Skills	Business Skills	Business Skills	Business Skills
Digital tech. (dummy)	0.137*** [0.035]						0.064** [0.027]					
Digital tech. (intensity)		0.050*** [0.010]						0.027*** [0.007]				
Software tech.			0.143*** [0.034]			0.131*** [0.034]			0.072*** [0.027]			0.065** [0.027]
Hybrid tech.				0.138*** [0.042]		0.118*** [0.042]				0.062** [0.031]		0.049 [0.031]
Machine tech					0.004 [0.050]	- 0.037 [0.049]					0.026 [0.036]	0.006 [0.036]
Revenues (log)	0.043*** [0.012]	0.039*** [0.012]	0.042*** [0.012]	0.045*** [0.012]	0.046*** [0.012]	0.042*** [0.012]	0.020** [0.008]	0.017** [0.008]	0.020** [0.008]	0.021** [0.008]	0.021*** [0.008]	0.019** [0.008]
Labour productivity	- 0.000 [0.000]	- 0.000 [0.000]	- 0.000 [0.000]	- 0.000 [0.000]	- 0.000 [0.000]	- 0.000 [0.000]	- 0.000 [0.000]	- 0.000 [0.000]	- 0.000 [0.000]	- 0.000 [0.000]	- 0.000 [0.000]	- 0.000 [0.000]
Integration	0.088*** [0.029]	0.086*** [0.029]	0.090*** [0.029]	0.097*** [0.029]	0.098*** [0.029]	0.092*** [0.029]	0.033 [0.022]	0.033 [0.022]	0.034 [0.022]	0.037* [0.022]	0.036 [0.022]	0.034 [0.022]
ROA	0.000 [0.001]	0.001 [0.001]	0.000 [0.001]	0.000 [0.001]	0.001 [0.001]	0.000 [0.001]	- 0.000 [0.001]	- 0.001 [0.001]	- 0.000 [0.001]	- 0.001 [0.001]	- 0.000 [0.001]	- 0.001 [0.001]
Family firm	- 0.031 [0.040]	- 0.035 [0.041]	- 0.035 [0.041]	- 0.049 [0.041]	- 0.023 [0.041]	- 0.038 [0.030]	- 0.038 [0.030]	- 0.033 [0.030]	- 0.037 [0.030]	- 0.037 [0.030]	- 0.043 [0.030]	- 0.033 [0.031]
Age	- 0.002** [0.001]	- 0.002** [0.001]	- 0.002** [0.001]	- 0.002** [0.001]	- 0.002** [0.001]	- 0.001* [0.001]	- 0.001* [0.001]	- 0.001* [0.001]	- 0.001* [0.001]	- 0.001 [0.001]	- 0.001* [0.001]	- 0.001* [0.001]
Observations	924	924	924	924	924	924	924	924	924	924	924	924
Industrial dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 3 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	Technical Skills	Technical Skills	Technical Skills	Technical Skills	Technical Skills	Technical Skills	Business Skills	Business Skills	Business Skills	Business Skills	Business Skills	Business Skills
Regional dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R2	0.0774	0.0774	0.0794	0.0729	0.0630	0.0866	0.0505	0.0505	0.0531	0.0477	0.0426	0.0569

Dependent variable: acquisition of new technical skills by 2022 (columns 1–6) and acquisition of new business skills by 2022 (columns 7–12); ***$p<0.01$, **$p<0.05$, *$p<0.1$; robust standard errors in brackets; the regressors are measured in 2019

Table 4 Technology adoption and provision of technical skills (average marginal effects of probit estimates)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	Technical Training	Technical Training	Technical Training	Technical Training	Technical Training	Technical Hiring	Technical Hiring	Technical Hiring	Technical Hiring	Technical Hiring
Digital tech.	0.074** [0.029]					0.079*** [0.028]				
Software tech.		0.085*** [0.028]			0.075*** [0.028]		0.074*** [0.027]			0.073*** [0.027]
Hybrid tech.			0.080*** [0.031]		0.064** [0.031]			0.050 [0.032]		0.043 [0.033]
Machine tech				0.041 [0.038]	0.017 [0.037]				- 0.044 [0.039]	- 0.059 [0.040]
Firm characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	924	924	924	924	924	910	910	910	910	910
Industrial dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Regional dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R2	0.102	0.105	0.102	0.0955	0.111	0.0455	0.0449	0.0369	0.0351	0.0503

Dependent variable: acquisition of new technical skills by 2022 through training (columns 1–5) and through hiring (columns 6–10); ***$p<0.01$, **$p<0.05$, *$p<0.1$; robust standard errors in brackets; the regressors are measured in 2019; firm-level characteristics are: revenues, labour productivity, new functions, ROA, family firm dummy, firm age

4.2 Robustness checks

In this section, we conduct several robustness checks to reinforce and extend the results of the main regression analysis presented in Sect. 4.1. Specifically: we conduct a bivariate probit regression to assess whether and to what extent the demand for a specific skill type is influenced by/conditional upon the demand for the other one (4.2.1); we adopt an instrumental variable (IV) approach to further address potential endogeneity issues (4.2.2); we use, as alternative key regressors, the resulting items of the factor analysis to assess whether the results are consistent with our main findings (4.2.3); we assess whether the potentially varying impact of the Covid-19 pandemic by sector has led to between-firm heterogeneity in terms of skill requirements or has moderated the relationship between technology adoption and skill acquisition (4.2.4); we check whether the main results hide significant sectoral heterogeneity that may hinder the generalizability of the findings (4.2.5).

4.2.1 Bivariate probit regression

Since the demand for one skill type may be influenced by the demand for the other one, the joint estimate of Eqs. [1] and [2] through a bivariate model can provide more consistent results if the two dependent variables are correlated (Ashford & Sowden, 1970; Meng & Schmidt, 1985).[9] Accordingly, we run a bivariate probit regression using *Technical_Skills* and *Business_Skills* as jointly determined dependent variables. However, the correlation between the error terms of Eqs. [1] and [2 shows a low statistical significance (p-value close to 0.1), which we consider too low to replace the probit model presented in Sect. 3.2 with a bivariate model.

4.2.2 IV regressions

Although the time lag between the regressors (measured in 2019) and the dependent variables (observed in 2022) can mitigate simultaneity concerns, endogeneity may still arise between the adoption of digital technologies and skill requirements, for instance, due to omitted-variable bias. We address this issue by estimating an IV regression model in which the instrumental variable is the share of online sales over total sales (measured in 2014) measured in the NUTS-3 region (province) where the firm is located. In this respect, we believe it is reasonable to assume that competitive pressure from digitalised firms operating in the same geographical area can spur a company's pace of technology adoption without directly affecting its skill demand. More specifically, an increase in online sales within a province is expected to generate positive spillovers for neighbouring firms, thereby stimulating their adoption of digital technologies. At the same time, there is no particular reason to expect that online sales in external organizations would trigger the acquisition of new skills in the absence of the prior introduction of digital technologies into the production process over the period between the two observations (i.e., 2014 and 2022).

[9] For more information on the bivariate probit model, see Cameron & Trivedi (2005). The results of the bivariate probit regression are available upon request.

Table 5 Technology adoption and provision of business skills (average marginal effects of probit estimates)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	Business Training	Business Training	Business Training	Business Training	Business Training	Business Hiring	Business Hiring	Business Hiring	Business Hiring	Business Hiring
Digital tech.	0.016 [0.019]					0.052** [0.022]				
Software tech.		0.020 [0.019]			0.015 [0.018]		0.056** [0.022]			0.054** [0.022]
Hybrid tech.			0.039** [0.020]		0.037* [0.020]			0.017 [0.024]		0.007 [0.024]
Machine tech				0.008 [0.024]	- 0.002 [0.025]				0.016 [0.027]	0.007 [0.027]
Firm characteristics	0.026*** [0.006]	0.025*** [0.006]	0.025*** [0.006]	0.026*** [0.006]	0.025*** [0.006]	- 0.005 [0.005]	- 0.005 [0.005]	- 0.004 [0.005]	- 0.004 [0.005]	- 0.005 [0.005]
Observations	915	915	915	915	915	924	924	924	924	924
Industrial dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Regional dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R2	0.0657	0.0668	0.0721	0.0642	0.0737	0.0760	0.0787	0.0628	0.0624	0.0791

Dependent variable: acquisition of new business skills by 2022 through training (columns 1–5) and through hiring (columns 6–10); ***$p<0.01$, **$p<0.05$, *$p<0.1$; robust standard errors in brackets; the regressors are measured in 2019; firm-level characteristics are: revenues, labour productivity, new functions, ROA, family firm dummy, firm age

The results of the IV regression (Table 7) suggest that the adoption of I4.0 technologies is a relevant antecedent of the acquisition of both technical and business skills. The results still hold when the standard errors are clustered at the NUTS-3 regional level (see columns 3 and 4) to account for potential Moulton-type bias (Moulton, 1990).[10] Similar findings are obtained when using online sales measured in 2019 as an instrument; however, to mitigate simultaneity concerns, we focus on the indicator referring to 2014.

4.2.3 Regressions based on the results of a factor analysis

To check the consistency of our classification of digital technologies, which may present some degree of subjectivity, we re-estimate [1] and [2] after replacing the dummies measuring the previously identified three technology types with the three items of a factor analysis (for more information, see Appendix 3). Each of the three factors is significantly related to one of the previously used technology categories. Also, as shown in Table 8, the results of the regression using the factors are strongly aligned with the main findings reported in Table 3; in particular, they confirm that both software and hybrid technologies increase firm's probability to introduce technical skills and, to some extent, business skills too, with hybrid technologies more strongly associated with the first of the two skill types. The insignificance of machine-based technologies is confirmed as well.

4.2.4 Assessing the potential influence of the Covid-19 pandemic

The three-year interval separating the two survey waves coincided with a particularly disruptive and adverse shock, namely, the outbreak of the COVID-19 pandemic. Accordingly, we examine whether the pandemic had heterogeneous effects across firms depending on their sectoral exposure to lockdown-related closures and supply-chain disruptions. Specifically, using information from the official document titled *'List of Suspended Activities Coronavirus'* (*'Elenco attività sospese Coronavirus'*),[11] we constructed, at the NACE 2-digit level, a dummy variable equal to 1 if the economic activity of firms operating in that sector was entirely or mostly suspended during the months following the outbreak of the COVID-19 pandemic, as mandated by the ministerial decree issued on March 25, 2020.

Examining columns 1 and 3 of Table 9 we find that, unsurprisingly, firms that were forced to temporarily suspend their activities in the aftermath of the COVID-19 outbreak are associated with a lower probability of introducing new technical and

[10] According to Moulton (1990), it is reasonable to expect that units sharing an observable characteristic, such as industry or location, also share unobservable characteristics that would lead the regression disturbances to be correlated.

[11] This document (available at this link: https://www.certifico.com/news/elenco-attivita-sospese-coronavirus), lists the Ateco (Nace Rev.2) codes of the Italian sectors that were allowed to operate also during the harshest phases of the Covid-19 pandemic because they were considered as essential for the functioning of the economy (e.g., "Food products, beverages and tobacco"; "Wood and paper products, printing and reproduction of recorded media"; "Electricity, gas, steam and air-conditioning supply"; "Financial and insurance activities"; "Education, human health and social work activities").

Table 6 Overview of skill requirements by technology category and mechanism of skill provision

Variables	Technical Skills	Technical Training	Technical Hiring	Business Skills	Business Training	Business Hiring
Digital tech.	pos (***)	pos (**)	pos (***)	pos (***)	not signif	pos (**)
Software tech.	pos (***)	pos (**)	pos (**)	pos (***)	not signif	pos(**)
Hybrid tech.	pos (***)	pos (***)	not signif	pos (**)	pos (**)	not signif
Machine tech	not signif	not signif	not signif	not signif	not signif	not signif

This table summarises the main results of the various combinations of digital technologies macro categories, skill types and mechanisms of skill provision reported in Tables 3, 4 and 5; ***p<0.01, **p<0.05, *p<0.1

Table 7 Adoption of digital technologies and skill requirements, IV probit regressions

	(1)	(2)	(3)	(4)
	Technical skills	Business skills	Technical skills	Business skills
Main regression				
Digital tech.	2.121*** [0.475]	2.302*** [0.177]	2.121*** [0.470]	2.302*** [0.179]
Constant	8.398** [3.310]	6.658*** [2.476]	8.398** [3.381]	6.658** [2.805]
First-stage regression instrument: online sales in 2014				
Online sales	0.001** [0.000]	0.001** [0.000]	0.001** [0.000]	0.001** [0.000]
Constant	- 3.357*** [0.735]	- 3.357*** [0.735]	- 3.357*** [0.760]	- 3.357*** [0.760]
athrho2_1	- 1.031 [0.664]	- 1.560** [0.651]	- 1.031 [0.657]	- 1.560** [0.652]
lnsigma2	- 0.862*** [0.019]	- 0.862*** [0.019]	- 0.862*** [0.019]	- 0.862*** [0.019]
Wald test of exogeneity	2.41*	5.74**	2.46*	5.74**
First-stage F-statistics	2.93	2.93	2.93	2.93
Prob>F	0.0875	0.0875	0.0875	0.0875
Anderson–Rubin (AR) test	2.86	5.91	2.86	5.91
P-value	0.0905	0.0150	0.0905	0.0150
Residuals KS-statistics (test of exclusion restriction)	0.905	0.987	0.905	0.987
P-value	0.523	0.558	0.523	0.558
Observations	914	914	914	914
Regional dummies	Yes	Yes	Yes	Yes
Industrial dummies	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes
Clusterisation level of standard errors			Regional (Nuts-3)	Regional (Nuts-3)
Chi2	354.524	603.301	663.694	1125.461

Dependent variable: acquisition of new technical skills by 2022 (columns 1 and 3) and new business skills (column 2 and 4); ***p<0.01, **p<0.05, *p<0.1; robust standard errors in brackets; the instrumental variable (share of online sales on total sales in the firm's Nuts3 region) is measured in 2014, while firm-level characteristics (revenues, labour productivity, new functions, ROA, family firm dummy and firm age) are measured in 2019; the first-stage F statistics were obtained by running a linear regression using the same variables. The test of the exclusion restriction is based on D'Haultfœuille et al. (2024)

Table 8 Adoption of technology types based on factor analysis and skill demand (average marginal effects of probit estimates)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Technical skills	Technical skills	Technical skills	Technical skills	Business skills	Business skills	Business skills	Business skills
Factor capturing software tech	0.064*** [0.014]			0.065*** [0.014]	0.038*** [0.011]			0.038*** [0.011]
Factor capturing hybrid tech		0.047*** [0.015]		0.051*** [0.014]		0.021** [0.010]		0.022** [0.010]
Factor capturing machine tech			- 0.013 [0.014]	- 0.014 [0.013]			0.004 [0.010]	0.003 [0.009]
Firm characteristics								
Observations	924	924	924	924	924	924	924	924
Industrial dummies	YES	YES	YES	YES	YES	YES	YES	YES
Regional dummies	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R2	0.0812	0.0731	0.0638	0.0936	0.0598	0.0475	0.0422	0.0665

Dependent variable: acquisition of new technical skills by 2022 (columns 1–4) and acquisition of new business skills by 2022 (columns 5–10); ***p<0.01, **p<0.05, *p<0.1; robust standard errors in brackets; the three main regressors are the results of a three-factor factor analysis; firm-level characteristics are: revenues, labour productivity, new functions, ROA, family firm dummy, firm age

Table 9 Skill requirements and the Covid-19 pandemic (probit estimates)

	(1)	(2)	(3)	(4)
Variables	Technical skills	Technical skills	Business skills	Business skills
Digital tech.	0.432*** [0.116]	0.556*** [0.167]	0.323** [0.145]	0.190* [0.140]
Sectoral closure after Covid-19	- 0.212* [0.124]	- 0.061 [0.173]	- 0.193* [0.113]	- 0.481* [0.255]
Digital tech. * sectoral closure after Covid-19		- 0.243 [0.231]		0.287 [0.287]
Firm characteristics	YES	YES	YES	YES
Observations	924	924	924	924
Regional dummies	YES	YES	YES	YES
Pseudo R2	0.08	0.081	0.056	0.06

Dependent variable: acquisition of new technical skills by 2022 (columns 1 and 2) and acquisition of new business skills by 2022 (columns 3 and 4); ***p<0.01, **p<0.05, *p<0.1; robust standard errors in brackets; since the interpretation of the average marginal effects may be challenging when interaction terms are used, we decided to directly report the estimated coefficients of the probit regressions rather than the corresponding average marginal effects business skills (even though the statistical magnitude of the coefficient of "sectoral exposure" is low). However, the lack of statistical significance of the interaction term in columns 2 and 4 suggests that the pandemic outbreak did not alter the relationship between digital adoption and skill acquisition.

4.2.5 Assessing potential sectoral heterogeneity

Finally, we check whether the main results hide significant sectoral heterogeneity that may hinder the generalisability of the findings. Accordingly, in this robustness check we introduce, among the control variables, a dummy equal to 1 if a company operates in the manufacturing sector (i.e., Nace 2-digit sectors ranging from 10 to 33), as well as its interaction with our key regressors measuring technology adoption. Table 10 (which does not report estimates for machine-based technologies, as they are never significant in the main analysis) shows that the interaction terms between the manufacturing dummy and the technology-adoption dummies are never statistically significant, suggesting that our main results are not sector-driven and hold for the Italian economy as a whole.

Table 10 Technology adoption and skill provision in manufacturing and non-manufacturing companies (probit estimates)

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Technical Skills	Technical Skills	Technical Skills	Business Skills	Business Skills	Business Skills
Manufacturing (dummy)	- 0.058 [0.422]	0.029 [0.419]	- 0.098 [0.419]	- 0.420 [0.487]	- 0.427 [0.478]	- 0.533 [0.452]
Digital tech.	0.435*** [0.208]			0.373** [0.170]		
Digital tech. * Manufacturing	0.040 [0.236]			- 0.119 [0.298]		
Software tech.		0.475*** [0.145]			0.400** [0.168]	
Software tech. * Manufacturing		- 0.016 [0.229]			- 0.079 [0.295]	
Hybrid tech.			0.453*** [0.159]			0.359** [0.183]
Hybrid tech. * Manufacturing			- 0.009 [0.318]			- 0.115 [0.377]
Firm characteristics	YES	YES	YES	YES	YES	YES
Observations	924	924	924	924	924	924
Industrial dummies						
Regional dummies	YES	YES	YES	YES	YES	YES
Pseudo R2	0.0538	0.0564	0.0513	0.0416	0.0441	0.0387

Dependent variable: acquisition of new technical skills by 2022 (columns 1–3) and acquisition of new business skills by 2022 (columns 4–6); ***p<0.01, **p<0.05, *p<0.1; robust standard errors in brackets; since the interpretation of the average marginal effects may be challenging when interaction terms are used, we decided to directly report the estimated coefficients of the probit regressions rather than the corresponding average marginal effects

5 Conclusions

The consequences of technological change for human capital have long been the subject of lively debate among scholars, practitioners, and policymakers. This discussion has gained new momentum with the advent of the Fourth Industrial Revolution, which has been characterised by unprecedented speed and pervasiveness. In particular, building on and advancing the SBTC framework, an increasing number of empirical studies have sought to identify the skills regarded as essential or particularly valuable for effectively operating in this increasingly digitalized and competitive business environment. At the same time, the literature has tried to understand whether technology adoption has prompted firms to train their workers and/or acquire new skills by hiring new personnel. However, to the best of our knowledge, a comprehensive analysis of technology adoption and skill requirements that, within a single framework, considers different types of both technologies and skills and breaks down skill provision into external and internal sources has not yet been conducted. In this work, we aim to fill this gap by drawing on firm-level information, mostly from a two-wave, unique survey.

From our regression analysis, which is supported by various robustness checks, it emerges that the adoption of new digital technologies is associated with the acquisition of both technical and business skills. Importantly, significant heterogeneity emerges across technological types and skill provision mechanisms: we see that software technologies, which not only support workers in performing technical activities but also affect how they interact with other employees and customers, require both technical and business skills. Business competencies, in particular, are more easily transferable across firms, thus reducing employers' incentive to finance training interventions and leading them to source such skills in the external labour market. Conversely, hybrid technologies (e.g., IoT), which often involve a remarkable degree of technical complexity and human–machine interaction, are more closely related to the integration of new technical skills, which are typically firm-specific and rarely transferable across companies. Finally, the adoption of machine-based technologies, on the contrary, never stimulates demand for new skills, probably because the displacement effect outweighs the reinstatement effect.

Overall, this study contributes to existing literature by providing a more in-depth understanding of I4.0-related skill needs and the underlying channels of skill acquisition. This could help identify the competencies that are worth reinforcing or acquiring in the presence of specific digital technologies: from the workers' perspective, our results can support employees in making decisions about their training investments. Meanwhile, they can guide firms in predicting the skill needs associated with various types of digital technologies and choosing the most appropriate skill provision mechanism.

In light of these considerations, policymakers should support companies adopting I4.0-related technologies to implement on-site training interventions that reinforce their workforce's technical skills. Such policy tools can include fiscal incentives, cost reductions, and financial subsidies. Policy interventions should also aim to encourage companies to invest, especially in software and hybrid technologies, which, compared to machine-based technologies, are associated with skill acquisition and labour creation. At the same time, policymakers may facilitate qualitative matching between employers and employees in occupations that require complex business skills, for instance, by creating and effectively monitoring a network of local recruitment agencies. Higher education institutions can also be involved through the activation of internship programs specifically designed to combine the managerial skills acquired through formal education with more hands-on knowledge of the digital technologies used by the host firms. All in all, these initiatives should help improve the match between labour demand and supply, especially in the current context characterised by significant complexity and uncertainty.

Our work also presents some limitations. First, the main data source is a survey, which inevitably introduces some subjectivity and covers only a relatively small portion of Italian firms. Also, although our sample is observed at two different points in time, the empirical analysis is cross-sectional. Moreover, residual endogeneity may remain a significant issue also due to unobserved firm-level characteristics that may influence both technology adoption and skill acquisition, and the estimated relationships should be regarded more as correlations than causal links. Future research may further investigate this topic using a larger and/or a longitudinal sample and combining firm-level and individual data.

Appendix 1. The survey

Sample selection and data collection

In this section, we integrate Sect. 3.1 by providing a more detailed overview of the process of sample selection and data collection carried out to obtain the survey dataset referring to the first wave of the survey.

In early 2019, we devised a survey aimed to shed light on relevant business aspects of Italian manufacturing companies that are often hardly assessable due to limited data availability, such as the firm's position in the value chain in terms of the major type of production, value contribution and ties with clients, business model innovation, technological innovation and environmental innovation. To this end, between May and June 2019, we first ran a pilot test aimed to assess the functionality of the online platform on which we intended to upload the questionnaire. Then, using the AIDA-Bvd database, we selected Italian companies operating in the manufacturing sector and industry-related sectors according to the Ateco/NACE Rev.2 classification (i.e., firms whose 2-digit Ateco/NACE ranges between 10 and 33 and firms with Ateco/NACE 62, 63 and 71), and whose number of employees in 2019 ranged between 10 and 1000. By applying these criteria, we expected to obtain an initial sample characterized by a good degree of representativeness of the Italian manufacturing sector and which, at the same time, would have been handleable for our purpose. The number of companies that fulfilled both the criteria amounted to 55,124. The sample distribution by NUTS-2 region and class size is shown in Table 11.

The data collection process was carried out between October 2019 and January 2020. In order to obtain more accurate and reliable answers and to increase the chances of obtaining a reply, we set up a team of post-graduate students with professional experience in the field; under our supervision, they contacted the entrepreneurs or managers of the selected companies and provided assistance during the answering process. The firms were reached either via telephone or via e-mail. Through the first method, which we applied to the selected companies whose number of employees in 2019 was equal or higher than 50 (i.e., about 11,700 firms), the analysts managed to establish a direct, effective and customized communication, during which they could provide useful information and clarify potential doubts; at the end of the conversation, they asked the respondents to provide them with a corporate e-mail address to which they would electronically send the link to the questionnaire.

Throughout the data collection process, the analysts meticulously monitored the completion status of the questionnaires and the response rate and sent reminders to the companies whose questionnaire was still incomplete. This method thus increased the probability to successfully involve the selected firms and obtain accurate and timely responses.

Regarding the second approach, an e-mail was sent to small companies, i.e., with a number of employees in 2019 lower than 50, containing information about the questionnaire and the link to the online platform. To ensure a higher response rate, reminder e-mails were sent to the companies that had not completed the questionnaire within the established deadlines. At the conclusion of the data collection process, we ended up with 16,492 questionnaires (out of the initial sample of 55,124 firms); hence, the response rate amounted to about 29.9%. We then checked the answers and discarded the questionnaires that were significantly incomplete or that contained potentially unreliable information, as well as duplicates and firms that, in the meantime, exited the market. in doing so, we obtained 8509 usable questionnaires.

We checked the representativeness of the sample of respondents (made up of 8509 companies) by comparing the firms' distribution of both these samples with the distribution observed in our initial dataset collected from Aida (i.e., the 55,124 firms stated above) and the distribution based on national data on Italian manufacturing firms compiled by the Italian National Statistical Office (ISTAT), which are supposed to convey the most exhaustive picture. To this end, for each of these samples, we computed the share of small and medium-sized enterprises (SMEs), i.e., firms with more than 10 employees but less than 250 employees. We find that the share of SMEs is at least equal to 97% in all the four datasets under scrutiny, confirming a well-known feature of the Italian economy. Also, the firms' distribution across Italian NUTS-2 regions is quite comparable across the datasets.

Finally, we matched the usable information with balance-sheet data (e.g., firm size, revenues, ROA, year of incorporation, etc.) retrieved from the commercial database AIDA-Bureau van Dijk (BvD). In doing so, we ended up with a sample of 4,214 firms for which both survey and financial information was available.

Sample representativeness

We assess the representativeness of the initial sample (n = 4214) and the final sample (n = 934) by comparing their sectoral distribution with that of the reference population (n = 55,124). To this end, for each sample, we run a chi-square goodness-of-fit test to evaluate whether the observed sectoral composition deviates significantly from the population structure.

Given the large sample sizes, statistical significance is expected even in the presence of relatively small deviations. Therefore, the interpretation primarily relies on the magnitude of the effect, measured using Cramér's V. The results indicate that the effect sizes are small for the initial sample of 4,214 companies (Cramér's V = 0.053), and small to moderate for the final sample comprising 934 units (Cramér's V = 0.069), suggesting limited substantive deviations from the population distribution. Overall, both samples can be considered sufficiently representative for analytical purposes. The n = 4214 sample shows greater coherence with the population sectoral structure and greater stability across smaller sectors, while the n = 934 sample exhibits slightly larger deviations, particularly in less populated sectors. This lower representativeness of the final sample may also be due to its small size, which did not allow us to carry out operations aimed at better balancing and consistency with the initial population. Anyway, both samples should be considered suitable for empirical analyses, with the first providing a slightly more robust approximation of the population structure. More information on this comparison is provided in Table 12.

Table 11 Distribution of the initial sample by region and size class (2019).Source: authors' elaboration of data from Aida-Bvd

	Number of employees					
NUTS-2 Regions (company headquarters)	10–49	50–99	100–249	250–1.000	not available	Total
Piemonte	3472	580	377	138	16	4583
Valle d'Aosta/Vallée d'Aoste	36	7	5	2	0	50
Lombardia	11,781	2044	1230	469	24	15,548
Trentino-Alto Adige/Südtirol	613	111	83	38	1	846
Veneto	6233	1091	549	184	9	8066
Friuli-Venezia Giulia	1060	182	107	44	1	1394
Liguria	508	73	39	14	1	635
Emilia-Romagna	4845	785	479	189	7	6305
Toscana	3662	410	214	68	10	4364
Umbria	652	96	58	14	1	821
Marche	1942	240	127	40	2	2351
Lazio	2004	293	153	67	15	2532
Abruzzo	803	81	51	25	2	962
Molise	107	6	3	1	0	117
Campania	2258	263	151	33	14	2719
Puglia	1586	175	62	34	7	1864
Basilicata	179	24	8	3	0	214
Calabria	285	22	8	1	0	316
Sicilia	889	87	38	8	3	1025
Sardegna	356	29	18	6	3	412
Total	43,271	6599	3760	1378	116	55,124

Deviations are concentrated in a small number of sectors, with underrepresentation in traditional manufacturing and overrepresentation in technology- and knowledge-intensive activities, particularly in the smaller sample. In both samples, traditional manufacturing sectors—most notably food manufacturing, basic metals, and motor vehicles—tend to be underrepresented relative to their population shares. Conversely, knowledge-intensive and technology-related activities, including computer and electronic products, machinery and equipment, scientific research and development, and ICT-related services, are generally overrepresented, particularly in the n = 934 sample. These discrepancies are more pronounced in smaller sectors and in the smaller sample, reflecting higher sampling variability. Importantly, deviations remain limited in magnitude and do not affect the overall sectoral coverage of the samples.

The following figure and table (Fig. 3 and Table 13) offer a more detailed overview of the sectoral distribution across the population of firms representing the starting point of our analysis and the two samples.

Table 12 Main metrics for assessing sample representativeness

Indicator	N = 4214 sample	N = 934 sample
Population size	55,124	55,124
Sample size	4214	934
Number of sectors	29	29
χ^2 goodness-of-fit test	334.19	124.02
Degrees of freedom	28	28
p-value	< 0.001	< 0.001
Cramér's V	0.053	0.069
Stability in small sectors	High	Moderate

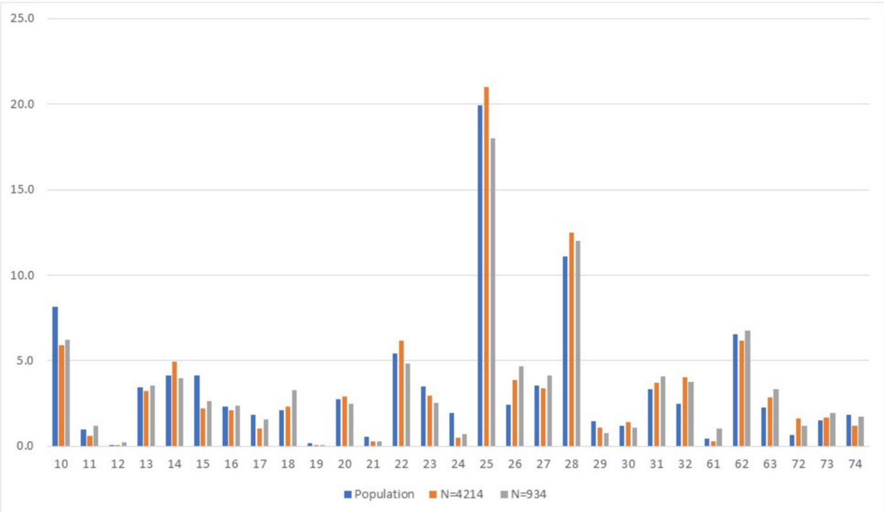

Fig. 3 Sectoral distribution across the initial population of firms and the two samples. Source: authors' elaboration of data from Aida-BvD and the survey

Table 13 Sectoral distribution of the population of firms and the two samples.Source: authors' elaboration of data from Aida-BvD and the survey

Sectors	NACE 2-digit	Population	Sectoral share of population	Sample A (N=4214)	Sectoral share of sample A	Sample B (N=934)	Sectoral share of sample B
Food manufacturing	10	4483	8.1	248	5.9	58	6.2
Beverages	11	531	1.0	26	0.6	11	1.2
Tobacco products	12	5	0.0	2	0.0	2	0.2
Textiles	13	1892	3.4	135	3.2	33	3.5
Wearing apparel	14	2271	4.1	207	4.9	37	4.0
Leather products	15	2290	4.2	93	2.2	25	2.6
Wood products	16	1286	2.3	88	2.1	22	2.4
Paper products	17	996	1.8	43	1.0	15	1.6
Printing and recorded media	18	1144	2.1	98	2.3	31	3.3
Coke and refined petroleum	19	107	0.2	3	0.1	1	0.1
Chemicals	20	1520	2.8	123	2.9	23	2.5
Pharmaceuticals	21	291	0.5	12	0.3	3	0.3
Rubber and plastics	22	2982	5.4	261	6.2	45	4.8
Non-metallic mineral products	23	1922	3.5	125	3.0	24	2.5
Basic metals	24	1070	1.9	21	0.5	7	0.7
Fabricated metal products	25	10,998	20.0	886	21.0	168	18.0
Computer, electronic and optical products	26	1344	2.4	162	3.8	44	4.7
Electrical equipment	27	1942	3.5	142	3.4	39	4.1
Machinery and equipment n.e.c	28	6125	11.1	527	12.5	112	12.0
Motor vehicles	29	800	1.5	46	1.1	7	0.7
Other transport equipment	30	664	1.2	60	1.4	10	1.1
Furniture	31	1828	3.3	157	3.7	38	4.1
Other manufacturing	32	1354	2.5	170	4.0	35	3.7
Telecommunications	61	235	0.4	11	0.3	10	1.0
Computer programming and consultancy	62	3606	6.5	261	6.2	63	6.7
Information services	63	1231	2.2	121	2.9	31	3.3

Table 13 (continued)

Sectors	NACE 2-digit	Population	Sectoral share of population	Sample A (N = 4214)	Sectoral share of sample A	Sample B (N = 934)	Sectoral share of sample B
Scientific R&D	72	372	0.7	68	1.6	11	1.2
Advertising and market research	73	824	1.5	71	1.7	18	1.9
Other professional, scientific and technical act	74	1011	1.8	49	1.2	16	1.7
Total		55,124	100.0	4214	100.0	934	100.0

The structure of the survey and the questions used in this study

The survey questionnaire comprises the following six distinct sections, each addressing specific aspects of the companies' operations and strategies:

(1) *Company's General Information*: it aims to provide an overview of the companies' financial performance and market dynamics by collecting information on variables such as firm turnover, export activities, and the impact of key customers on revenue generation;
(2) *Business model*: this section focuses on the changes made by companies to their business model in the previous years in four relevant functional areas;
(3) *Adopted or Planned Industry 4.0 Technologies*: this part of the questionnaire explores the effective or planned development and implementation of new digital and enabling technologies, such as Big Data, Cloud Computing, Cyber Security, Additive Manufacturing and (I4.0) Robots;
(4) *Data Management*: the fourth section aims to shed light on the importance of data analysis for the surveyed companies; to this end, it investigates the companies' approaches to data management and their utilization of data-driven decision-making processes;
(5) *Eco-Innovation*: this part explores the companies' alignment with environmentally friendly and "green" policies and practices;
(6) *Investment Policy*: the sixth section aims to advance our understanding of the company's willingness to invest in innovative technologies, processes, or market expansion.
(7) Information about the interviewee: this final section gathers some information (e.g., age, gender, role within the company) about the interviewee.

Below, following the survey structure, we report the survey questions, originally formulated in Italian and here translated in English, that we used in our study.

Section A. General information

A7. Concerning the ownership and management of the company:

– the firm can be defined as a family business.[12]
– the firm is not a family business.

Section B. Business Model

….

….

B4. In the past three years, the company has: (more options can be selected, but please select only the answers referring to the most significant changes):

[12] Following the "Manuale di Diritto di Famiglia", a family business can be defined as a business activity for which they collaborate, on regular basis, the spuse, the relatives (until the third degree) and relatives-in-law (until the second degree).

....
....

- Introduced new technical skills.[13]
- Introduced new business skills.[14]

B4c. Answer this question in case you previously answered that you introduced new technical and/or business skills:

In the past three years, the company has:

- Introduced new technical skills mainly through (on-the-job or external) training of its personnel.
- Introduced new technical skills mainly through hiring of new personnel.
- Introduced new business skills mainly through (on-the-job or external) training of its personnel.
- Introduced new business skills mainly through hiring of new personnel.

[…]

The answers to questions B4 and B4c were used to build our dependent variables measuring the introduction of new technical skills, the introduction of new business skills, technical hiring, technical training, business hiring and business training, respectively.

Section C. Industry 4.0 technologies

C1.1[15] Indicate the Industry 4.0 technologies that are already entirely adopted (i.e., whose adoption process was concluded in the past years):

- Internet of Things (IoT) and Big data Analytics (treated separately in the second wave of the survey);
- Management systems (e.g., ERP, MES, SCADA, PLM, SCM);
- Business Intelligence and CRM;
- Cloud Computing;
- IT security (especially cybersecurity);
- Industry 4.0 robots (including collaborative robots).

[13] Following the O*NET classification, with the term technical skills we refer to "Developed capacities used to design, set-up, operate, and correct malfunctions involving application of machines or technological systems". Examples of technical skills are: equipment maintenance; installation of equipment and programmes; operation and control of equipment and systems; analysis or monitoring of operations; software programming; quality control; technology design.

[14] The term business skills refer to a more heterogeneous category of cross-functional competencies that are typically required to effectively run a company. Drawing upon the O*NET classification, examples of business skills are: management of financial, material and/or personnel resources; social skills enhancing business activities, such as coordination and/or negotiation; systems skills (i.e., developed capacities used to understand, monitor, and improve socio-technical systems), such as judgment and decision making, systems analysis and systems evaluation.

[15] Question C1 also asks whether the firm is still undergoing a process of introduction of these I4.0 technologies.

– Additive manufacturing (e.g., 3D printing).
– Augmented Reality.

Artificial Intelligence (included only in the questionnaire administered through the second wave).

The answers to this question (referring to the first wave) were used to build our key regressors capturing the adoption of (any type of) digital technologies and the adoption of software technologies, hybrid technologies and machine-based technologies, respectively.

Appendix 2. Additional tables and figures

See Table 14 and Figs. 4, 5, 6.

Table 14 Pairwise correlations between the main variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Digital_Tech	1.000										
(2) Software_Tech	0.957*	1.000									
(3) Hybrid_Tech	0.220*	0.172*	1.000								
(4) Machine_Tech	0.185*	0.109*	0.136*	1.000							
(5) Digital_Tech	0.680*	0.681*	0.560*	0.363*	1.000						
(6) Techical_Skills	0.161*	0.171*	0.157*	0.022	0.232*	1.000					
(7) Business_Skills	0.083*	0.095*	0.074*	0.024*	0.136*	0.229*	1.000				
(8) Technical_Training	0.111*	0.125*	0.137*	0.048*	0.211*	0.691*	0.159*	1.000			
(9) Technical_Hiring	0.098*	0.095*	0.064*	-0.023*	0.085*	0.607*	0.138*	-0.155*	1.000		
(10) Business_Training	0.039*	0.048*	0.078*	0.021	0.131*	0.205*	0.664*	0.338*	-0.091*	1.000	
(11) Business_Hiring	0.073*	0.082*	0.024*	0.012	0.058*	0.110*	0.703*	-0.109*	0.270*	-0.064*	1.000

*p<0.5

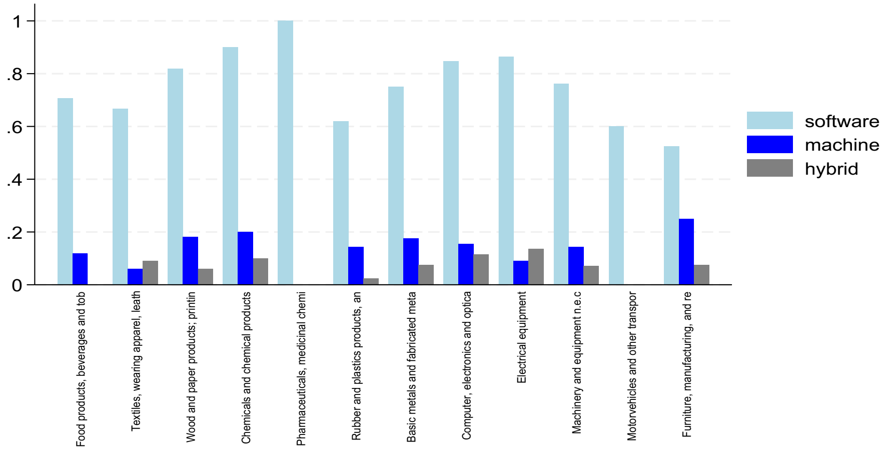

Fig. 4 Adoption of different types of digital technologies in the manufacturing (Nace 2-digit) sectors. Source: authors' elaboration of data from the survey. The sectoral codes are retrieved from Aida-Bvd

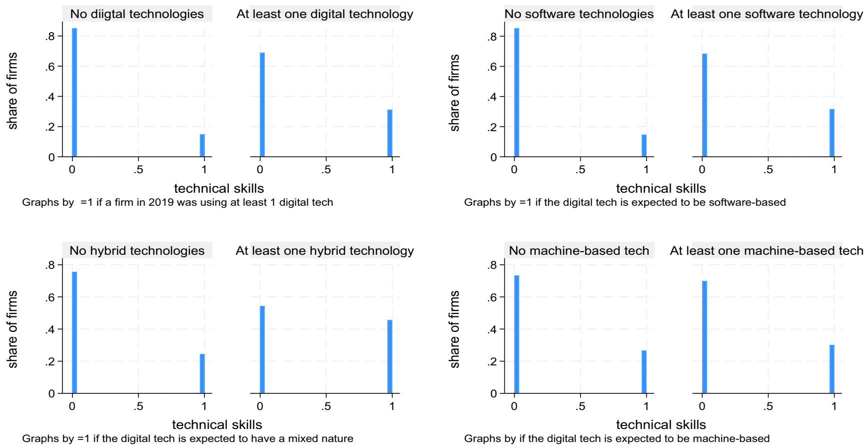

Fig. 5 Acquisition of technical skills by type of digital technology. Source: authors' elaboration of data from the survey

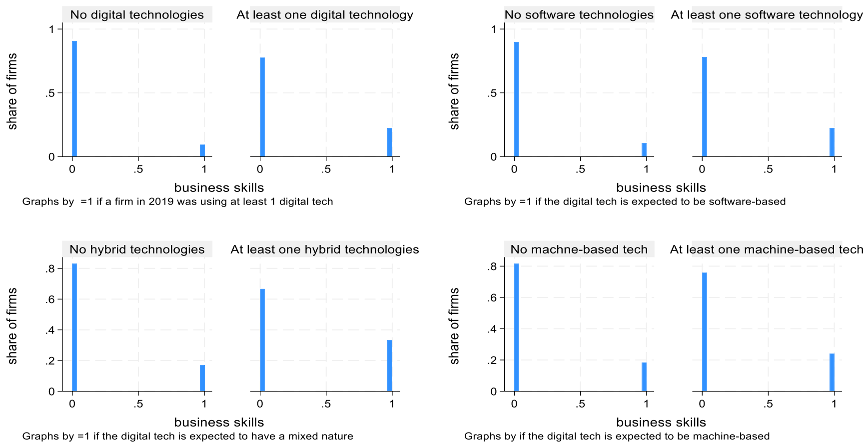

Fig. 6 Acquisition of business skills by type of digital technology. Source: authors' elaboration of data from the survey

Appendix 3. Additional information on the robustness checks performed in Sect. 4.2

In this Appendix, we shortly delve into the methodological issue of classifying our set of new digital technologies into three categories, captured by the covariates *Software_Tech*, *Hybrid_Tech* and *Machine_Tech*. Albeit consistent with previous studies and based on some well-known features of the technologies under scrutiny, we indeed acknowledge that the *ex-ante* construction of these variables may suffer some degree of subjectivity which can affect the results of the econometric analysis; hence, a robustness test on the validity of these covariates is needed, as suggested by the methodological literature on composite indicators (e.g. OECD, 2008). Accordingly, we apply the data-driven technique of factor analysis (FA) to generate three separate variables (factors) measuring the adoption of machine-based, hybrid, and software technologies, respectively.

In particular, after running the factor analysis and completing the orthogonal rotation of the three latent factors, we coded the latter according to the loadings of the original items, i.e., the individual technologies, after the rotation. Based on these outcomes (available upon request), we labelled Factor 1 as "hybrid technologies", Factor 2 as "software technologies", and Factor 3 as "machine-based technologies". All in all, the factor-based aggregation is consistent with our desk-based aggregation. The main difference lies in the fact that, in the FA, cloud computing enters the factor mainly associated with hybrid technologies, rather than the factor associated with software technologies. Table 15 reports the values of the rotated factor loadings and the unique variances.

In Sect. 4.2.3, we re-estimate our baseline models (Eqs. [1] and [2]) after replacing the three technological dummies with these factors.

Table 15 Pattern matrix of rotated factor loadings and unique variances

Digital technology	Factor 1	Factor 2	Factor 3	Uniqueness
IoT and Big Data Analytics	0.696	0.1173	0.0949	0.4928
ERP2019	0.0801	0.7217	0.189	0.437
Business Intelligence and CRM	0.5962	0.3791	- 0.0174	0.5005
Cloud Computing	0.6127	0.3521	- 0.1545	0.4768
Cyber Security	0.1219	0.7266	0.0011	0.4572
I4.0 robots	- 0.075	0.2075	0.7639	0.3677
Additive Manufacturing	0.2324	- 0.0955	0.6774	0.478
Augmented Reality	0.6258	- 0.2383	0.2508	0.4886

Funding Open access funding provided by Università Politecnica delle Marche within the CRUI-CARE Agreement. No funding was received for conducting this study.

Declarations

Conflict of interest The authors do not have conflicting interests to disclose.

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