Adoption of Digital Technologies and Skills in Greater Manchester:

Motivations, Barriers and Impact

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Executive summary

Digital technologies are increasingly being adopted by businesses in both the manufacturing and service industries, and their adoption affects and is affected by the availability of (digital) skills. This executive summary presents an overview of the main results of the bespoke survey on Adoption of Digital Technologies and Skills (ADiTS) in Greater Manchester. The survey represents a pioneering effort to identify the patterns of technology diffusion and the pervasiveness of six advanced digital technologies at the firm level: namely, Artificial Intelligence (AI), Big Data, Cloud Computing, 3D Printing, Internet of Things (IoT) and Robotics. The sample of respondents is mainly composed of private companies (88%), in the service sector (82%) including two-thirds classified as knowledge intensive services (KIS).

According to the survey, 78% of the firms located in Greater Manchester are digital technology (DT) adopters using at least one type of advanced digital technology. Adoption of DTs is led mainly by firms in knowledge-intensive service and high-tech manufacturing (KI-HT) sectors where 84% of firms have adopted at least one technology. Among the six digital technologies of interest, Cloud Computing is the most widespread, with adopters accounting for 70% of the respondents, including 42% of firms reporting high use of this technology. However, results reveal that different digital technologies are at different stages of diffusion. While Cloud Computing can be considered to be at a rather advanced stage of diffusion, other technologies are at earlier stages of adoption. For example, Big Data and AI are the second most adopted technologies (25%), but they are mainly in a testing/low-use phase rather than having been adopted for high/medium use.

There appear to be complementarities among digital technologies, as 43% of adopters reported adopting two or more digital technologies. In particular, a quarter of the firms adopted two of them and 18% adopted three or more. The most frequent combinations of technologies are Cloud Computing and AI, and Cloud Computing and Big Data.

Looking at the motivations for adopting digital technologies, the main reason reported is related to innovative processes, with 67% of the firms having decided to adopt digital technologies to improve the quality or reliability of processes or methods. Product or service range expansion, and process or method upgrade are the following most common reasons to adopt (51% and 49% respectively). Task automation, which is often associated with the adoption of digital technologies (mainly around industrial robots), was selected as a motivation by 45% of the adopters. Processor method quality improvement is the main motivation for adopting AI (53%), Cloud Computing (54%) and IoT (50%), while in the case of Big Data and 3D Printing the main reasons are to expand the range of goods or products (57% and 56% respectively) and, in the case of Robotics, to upgrade outdated processes or methods (73%).

The report assesses two types of impact of the adoption of digital technologies: on productivity and on employment. The impact on productivity seems to occur in relation to the volume of production and number of customers (23% and 39% respectively), and product diversification and type of customers (32% and 30% respectively). In particular, Robotics and 3D Printing technologies impact mainly on the volume of products (82% and 56% respectively) and product diversification (45% and 56%), while Cloud Computing, Big Data and AI allow increasing the number of customers (43%, 40% and 37% respectively). At the same time, and especially shortly after adopting new technologies, there can be substantial increases in production costs and cost of processes for technologies like Cloud Computing and 3D Printing. These costs, in turn, increase the selling price of the goods and/or services.

Concerning employment, there appears to be a dilemma between quality and quantity. The survey found that 22% of the adopters experienced a positive increment in the number of employees, with 41% reporting growth in skilled workers (in particular for those adopting Robotics (91%), AI (53%), Cloud Computing (48%) and Big Data (47%)), and 27% particularly focusing on STEM (science, technology, engineering and mathematics) skilled workers. In this case, skills are becoming a remarkably important intangible asset for firms and, indeed, the lack of access to required human capital and skills has been reported as a significant barrier to adoption. In particular, among the barriers to adopting digital technologies, the cost of the digital technology and the lack of human capital are the most frequently selected (31% apiece). AI and Big Data were the most cost-sensitive technologies together with lack of access to human capital, skills and talent. While the cost of the technology seems to affect KI-HT sectors the most (34%), lack of skills is a common problem regardless of the sector (30%). Nonetheless, only one out of three firms has organised training activities related to digital technologies (particularly about Cloud Computing) and, among those that have done so, tailored on-the-job training is the most frequent option.

Looking at their needs for skills, adopters of digital technologies tend to rate higher both digital and non-digital skills, but key differences appear for skills related to problem solving (covering technical problems, identifying needs and technological responses, creativity and identifying competence gaps) in a digital environment, as well as practical traditional skills like numeracy, literacy, IT (information technology), reading and writing. Our survey also highlights that, among the adopters of digital technologies, digital skills constitute a relevant key asset, as they rate such skills higher, on average, than they rate traditional basic skills. In particular, different elements of safety (protecting devices, personal data and privacy, health and well-being, and environmental) play a key role.

In summary, the current report provides the first regional results of advanced digital technology adoption in the UK and its relationship to companies' skill sets. Not only does it shed light on the strategies for adopting digital technologies, but it also offers insights on the primary barriers experienced by enterprises, and the impact on employment and productivity these technologies might have. Using data collected on AI, Big Data, Cloud Computing, 3D Printing, IoT and Robotics, this report represents a first look at key statistics on their adoption across firms and sectors in Greater Manchester. It identifies which technologies are at the early stages of diffusion, providing some conclusions regarding technology adoption and firm characteristics and performance, as well as insights to advance the research frontier of technology diffusion in the digital era.

1. Introduction

Advanced digital technologies, such as Artificial Intelligence (AI), Big Data, Cloud Computing, 3D Printing/Additive Manufacturing, the Internet of Things (IoT) and Robotics, are changing the processes for developing, producing and delivering products and processes, and are considered important drivers of productivity, greater demand for human labour and improved job quality (Lane and Saint-Martin, 2021). Several studies have documented these changes, including variations in the structure of occupations and labour markets, whether new technologies complement or substitute for labour (Bessen, 2018; Lane and Saint-Martin, 2021), the types of skills required to respond or contribute to this transformation process, which tasks will be the most affected (Brynjolfsson et al., 2019), and which new competencies will be required (Felten et al., 2018).

Research in labour economics has long observed that technological change is skill-biased – that is, it increases the demand for educated and highly skilled workers compared to less-educated ones (Nelson and Phelps, 1966). However, recent evidence suggests that the destruction of jobs occurs in the middle of the occupation and skills distributions, usually for occupations that are highly routinised and easily replaced by automated processes (Autor et al., 2003), resulting in so-called job polarisation. This involves, for example, the case of robots ushering workers out of factories, but complementing other highly skilled jobs based on complex tasks such as scientific work. These dynamics have been reinforced by new digital paradigms and have been identified as one of the main factors in the structural transformation of occupations and labour markets (Autor and Dorn, 2013; Goos and Manning, 2007).

Adopting digital technologies and changes in skills could affect a firm's productivity. However, the potential effect of these advanced technologies is still far from evident, and authors like Brynjolfsson et al. (2019) suggest that, although AI holds great potential, there is little sign that these technologies have affected aggregate productivity statistics so far (the so-called "modern productivity paradox").

Based on the transformations observed in the employment structure and the potential of digital technologies to transform work, firms have started to reconsider their skills requirements. Workers may need to re-skill or up-skill to adapt to the reorganisation of tasks and the emergence of new tasks and jobs. Questions related to what digital-related skills, or what types of workers, will be needed have not been completely answered yet. At the same time, firms need to reassess whether they want to develop technologies internally or buy them from external sources, as well as to make decisions around training, outsourcing and recruitment.

Although firms are at the heart of these labour demand transformations (Matias Cortes and Salvatori, 2019), very little is known about how they actually respond or contribute to the skills transformation process, and the extent to which the new digital technologies paradigm accelerates the demand for more or re-skilled and specialised workers. We identify three limitations in the current literature on advanced digital technologies. First, with very few exceptions (see for example Zolas et al., 2020; Benassi et al., 2020), studies have been mainly conducted at aggregate levels using nationwide data or industry-level measures of robot diffusion (Acemoglu and Restrepo, 2020, Graetz and Michaels, 2018), information technology (Bessen, 2002) and patents (Autor and Salomons, 2018) as proxies for measuring the impact of automation on country-wide or industry-level total factor productivity. Second, in the economic literature, skills and tasks are often treated as interchangeable terms, where skills are defined as a vector of the different abilities needed to perform specific job tasks (Autor et al., 2003). However, most studies do not take into consideration the changes in workers' skills distribution that the adoption of digital technologies might require to maximise the positive gains of technology adoption. The third reason relates to the lack of data on the adoption of digital technologies (which is different from technology development as measured by, for example, patent data). Prior studies make the crucial assumption that all firms in a given industry and/or labour market have the same ability and willingness to adopt digital technologies. Lack of firm-level data has been cited as a critical impediment to understanding how digital technologies impact on workers and firms (Seamans and Raj, 2018). As some authors have recognised, "this data gap hinders evidence-based decision making at all levels of government and society" (Zolas et al., 2020, p.2). Importantly, we have limited knowledge about firms' decisions, including their motivations and barriers, to adopt these digital technologies.

The UK represents an interesting case because skills shortages have been recognised as a major issue (e.g., McGowan and Andrews, 2015), and this can significantly hamper firms' innovation, productivity and growth if there is a limited supply of workers with the particular skills to meet demand. According to McGowan and Andrews (2015), the UK could boost its productivity by five percent if it reduced the levels of skill mismatches to OECD best practice levels. At the regional level, this report provides insights specific to the Local Skills Improvement Plan (LSIP) in Greater Manchester, as it covers key elements to understanding current skills needs in relation to the adoption of digital technologies, a key element to strengthen understanding of local economic needs and shape skills provision following the Skills for Jobs White Paper (Department for Education, 2021).

In this report, we address these issues by drawing on original data based on a bespoke survey on firms in Greater Manchester (England). The objective of this study is then twofold: first, to understand the status quo of the use of digital technologies, including its effect on firms' employment and productivity; and, second, to shed light on the digital and non-digital skills needs that the adoption of digital technologies and labour transformations may require.

2. Industry 4.0, advanced digital technologies and skills

2.1 Industry 4.0

The fourth industrial revolution (4IR), also referred to as "Industry 4.0", is changing the way in which people work, live and interact, and is recognised as one of the most disruptive phenomena in recent times (Schwab, 2017). It refers to a set of multi-layered, intertwined, and possibly convergent technologies emerged in the last few decades (Gilchrist, 2016) which bring multiple advantages to a firm: they increase the firm's flexibility (Baldwin and Clark, 2000), improve the automation of their processes and reduce costs (Brynjolfsson and McAfee, 2014), and increase performance and productivity (Graetz and Michaels, 2018).

Digital technologies are assumed to be enabling technologies because of their potential for disruptive change. However, Martinelli et al. (2021) argue that currently only AI and Big Data present the key characteristics of pervasiveness, high dynamism and strong complementarities that characterise General Purpose Technologies (GPTs); other digital technologies do not seem to be fully developed yet to show GPT-like characteristics. Similarly, Cockburn et al. (2018) have found that AI is rapidly developing and has been applied in several (economically) relevant sectors, but that it still lacks the positive spillover effect to spawn innovation in its applications. Recently, scholars have concluded that although these digital technologies hold great potential, there is little sign that they have affected aggregate productivity statistics yet (Brynjolfsson et al., 2019) and that they may or may not lead to a radically new "techno-economic paradigm" (Dosi, 1988; Freeman and Perez, 1988).

Still, the literature demonstrates high potential for these advanced technologies, and has provided evidence on the evolution of 4IR-related technologies (Martinelli et al., 2021; EPO, 2020; Benassi et al., 2020). According to Benassi et al. (2020), within three decades, from 1985 to 2014, 4IR patent applications filed at the European Patent Office showed a tenfold increase from about 5,000 to roughly 50,000 per year, compared to overall patent applications that quadrupled in the same period.

Given the broad remit of 4IR technologies, the academic literature is not (yet) unanimous in providing a clear list of the technologies contained therein. In this study, we cover the main six advanced technologies of Industry 4.0 defined as follows:

- Artificial Intelligence (AI): A branch of computer science and engineering devoted to making machines intelligent (e.g., machine learning). Intelligence is that quality that enables an entity to perceive, analyse, determine a response and act appropriately in its environment, for example, writing algorithms for decision making.
- Big Data: Use of techniques, technology and software for the analysis of large volumes of rapidly changing information that can be obtained from sources within the enterprise or from other sources.
- Cloud Computing: Computing resources available on demand via the internet (e.g., networks, servers, storage, applications and services). For example, using cloud applications in Microsoft 365.
- 3D Printing/Additive Manufacturing: Use of special printers for the creation of three-dimensional physical objects by using additive layers

- Internet of Things (IoT): Devices with self-identification capabilities (localisation, status diagnosis, data acquisition, processing and implementation) that are connected via standard communication protocols.
- Robotics: Automatically controlled, reprogrammable and multipurpose machines used in automated operations in industrial and service environments, for example, automation in the assembly line.

Table 1 summarises relevant information for each type of digital technology as well as its applications.

Table 1. Definitions and applications of selected advanced digital technologies

Digital technology	Definition	Applications
Artificial Intelligence	A branch of computer science and engineering devoted to making machines intelligent. Intelligence is that quality that enables an entity to perceive, analyse, determine a response and act appropriately in its environment.	Systems with artificial intelligence perform functions including, but not limited to, speech recognition, machine vision or machine learning, e.g., speech recognition, machine vision using sensors and software, machine learning which uses statistical software and data to “learn” and make better predictions without reprogramming. AI technologies also include virtual agents, deep learning platforms, decision management systems, biometrics, text analytics, and natural language generation and processing.
Big Data	Use of techniques, technology and software for the analysis of large volumes of rapidly changing and varied information that can be obtained from sources within the enterprise or from other sources.	Big Data includes methods and tools to process large volumes of data for manufacturing, supply chain management and maintenance. The data can come from IoT systems connected to the productive layer (for example, with sensors and associated equipment), or the exchange between IT systems for production and warehouse management. Specific applications in this area are machine learning tools for planning and forecasting, predictive maintenance and simulation.
Cloud Computing	Cloud systems and applications are computing resources available on demand via the internet (e.g., networks, servers, storage, applications and services).	Cloud Computing enables ubiquitous, convenient, on-demand internet access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction. For example, using cloud applications in Microsoft 365.
3D Printing	Use of special printers for the creation of three-dimensional physical objects by using additive layers.	3D Printing finds application in the prototyping (to support the product development process, static simulation and wind tunnels, etc.), manufacturing (direct production of products), maintenance and repair, and modelling phases, e.g., drugs, medicine, dentistry, automotive sector, construction, customised tools and components. 3D Printing/additive manufacturing includes the following seven categories: Binder

		Jetting, Directed Energy Deposition, Material Extrusion, Material Jetting, Powder Bed Fusion, Sheet Lamination and Photo Polymerisation.
Internet of Things	Devices with self-identification capabilities (localisation, status diagnosis, data acquisition, processing and implementation) that are connected via standard communication protocols.	IoT technologies are used in manufacturing applications, and in many others (housing and construction, automotive sector, environment, smart city, agriculture, health, etc.).
Robotics	Robotic equipment (or robots) comprises automatically controlled, reprogrammable and multipurpose machines used in automated operations in industrial and service environments.	Robots may be mobile, incorporated into standalone stations, or integrated into a production line. A robot may be part of a manufacturing cell or incorporated into another piece of equipment. Industrial robots may perform operations such as: palletising, pick and place, machine tending, material handling, dispensing, welding, packing/repacking and cleanroom. Service robots are commonly used in businesses for such operations as cleaning, delivery, construction, inspection, and medical services such as dispensing or surgery.

2.2 The effect of digital technologies on employment and productivity

Digital technologies are becoming increasingly pervasive, causing substantial transformation in firms and economies, as well as labour markets and demand for skills. The literature exploring these dynamics has identified two main trends: (1) automation as a substitute for human labour (Autor et al., 2003); and (2) the effects of technological change on labour market dynamics (Van Roy et al., 2018). One generally accepted consequence of digital technologies is that the destruction of jobs occurs in the middle of the occupation and skills distributions, usually for those occupations that are highly routinised and easily replaced by automated processes, such as the tasks performed by operators in plant-based jobs. This phenomenon has been described as job polariation (Autor et al., 2015) and is one of the main factors in the structural transformation of occupations and labour markets (Autor and Dorn, 2013; Goos and Manning, 2007).

The literature on the determinants of employment polarisation and the effect on labour markets builds on the “task-based approach”, specifically in relation to the adoption of robots. This framework was initially developed in the context of Information and Communication Technologies (ICTs) as a substitute for human labour in “routine” tasks, which are at the core of middle-skill occupations such as clerks or machine operators (Autor et al., 2003). The more recent empirical research on the effects of technological change on labour market dynamics provides contrasting results, suggesting, on one hand, the labour-friendly nature of technological innovation (Van Roy et al., 2018) and, on the other hand, excess worker turnover having a negative impact on firms’ innovation dynamics (Grinza and Quatraro, 2019). Moreover, recent studies find that technology is not only destroying jobs, but it is also expanding the possibilities for creating demand for new occupations (Bessen, 2018; Acemoglu and Restrepo 2020; Klenert et al., 2020).

A second stream of literature focuses on the relationship between digital technologies and firms' performance. Industry 4.0 technologies are also having a strong impact on traditional jobs because, like ICTs, they require the reorganisation of work in traditional as well as high-tech sectors (e.g., robotisation in manufacturing). Several studies have analysed the relationship between digital technologies and productivity using aggregated data nationwide or industry-level measures of robot diffusion (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018), information technology (Bessen, 2002), and patents (Autor and Salomons, 2018) as proxies for degree of automation, on the country or industry-level total factor productivity. For example, Graetz and Michaels (2018) find that robot adoption within industries raises labour productivity and total factor productivity (TFP). Similarly, Ballestar et al. (2020) link the use of robots to labour productivity in Spanish small and medium manufacturing enterprises, finding associations between robotic devices and higher productivity and employment rates. More conservative voices question the potential of digital technologies in the current digital era, in particular AI, by arguing that there is still little effect on aggregate productivity that can be attributed to these technologies (Brynjolfsson et al., 2019).

2.3 Reconfiguring the skillset due to digital transformation

Since the adoption of digital technologies often leads to a transformation of activities and processes in firms, it also appears that skills such as creativity, flexibility and critical and problem-orientated thinking are becoming increasingly important to companies (OECD, 2017). In addition, higher and all-rounded skilled workers tend to adopt technology faster and make better use of it (Nedelkoska and Quintini, 2018). Re-skilling and up-skilling have become key processes to support innovation and growth, including through specific on-the-job training, calling for clear human resources and training strategies by managers to develop the right skill sets in-house, as well as envisioning new structures and processes to enable new combinations of different skills to support creativity and innovation.

In the literature, skills and tasks are usually treated interchangeably, as skills are defined as a vector of the different abilities needed to perform specific job tasks (Autor et al., 2003). However, most studies do not consider the changes in workers' skills distribution that the adoption of digital technologies might require to maximise their positive impact. Thus, our understanding of the interplay between digital technologies and skills, beyond a broad recognition of their complementarity, is still limited.

Researchers have studied the relationship between the adoption of advanced digital technologies and skills based on vacancies, which allow them to link job requirements with the tasks and skills needs in firms. Acemoglu et al. (2020) use establishment-level data on vacancies with detailed occupational information from 2010 onwards, and conclude that AI is altering the task structure of jobs, replacing some human-performed tasks and making certain skills redundant, while simultaneously generating new tasks requiring new skills. Similarly, other studies deal with recent advancements in AI and how these can affect the tasks performed by employees in the workplace (Brynjolfsson et al., 2019; Felten et al., 2021). For example, Felten et al. (2021) conclude that entire white-collar occupations requiring advanced degrees (such as genetic counsellors, financial examiners and actuaries) rely on abilities that are likely to be affected by advances in AI technology, while occupations in non-office jobs requiring a high extent of physical effort and exertion are less likely to be affected. According to Nicoletti et al. (2020), a complementarity exists between advanced technologies and skills, evidenced by the fact that digital technology adoption is more widespread in environments characterised by wider availability of ICT skills – especially ICT literacy and training of low-skilled workers.

Other studies have used data from the OECD Programme of the International Assessment of Adult Competencies (PIAAC) to understand the skills needs for the digital world. They find that the increasing use of digital technologies at work is raising the demand for new skills along three lines: 1) ICT specialist skills to programme, develop applications and manage networks; 2) ICT generic skills to use such technologies for professional purposes; and 3) ICT complementary skills to perform new tasks associated with the use of ICTs at work (OECD, 2017). Developing such skills could also become an important element of educational systems in many countries, calling for newly designed educational paths and curricula.

To conclude, skills requirements are changing within and across organisations and industries, making existing ones redundant or obsolete (Autor et al., 2015; Zysman and Kenney, 2018). Thus, a better understanding of the associations and dynamics between the adoption of digital technologies and associated skills is needed, to ensure that companies' current and future strategic skills needs are met, and to avoid stunted productivity and a negative impact on economic growth.

3. Methods

3.1 Data

This report is based on the data collected using a bespoke survey on the Adoption of Digital Technologies and Skills (ADiTS). The authors of this report designed the survey instrument ADiTS to comprise the following four sections.

General Information: In addition to standard general information on the organisation – e.g., industry, size, age and location – the survey asked about the educational qualifications and fields of the owner(s) and employees, as this could affect their propensity to adopt the emerging digital technologies investigated in the study.

Research and Development (R&D) and Innovation: The second section adapted its questions and definitions of R&D and innovation from the Office of National Statistics UK Innovation Survey, which is the UK's contribution to the European Union Community Innovation Survey (CIS). The CIS gathers information on the innovation of businesses. It was first introduced in 1993 and has been conducted in EU Member States biennially since 2004. In this section, respondents were asked about their participation in innovation activities, expenditure, the share of employees that are engaged in R&D, the introduction of product and process innovations, and protection for intellectual property.

Digital Technologies: This section asked about six advanced digital technologies (i.e., AI, Big Data, Cloud Computing, 3D Printing, IoT, and Robotics) with regard to their development, motivations for and barriers to adoption, and their effect on employment, skills and productivity in organisations. This section was adapted from the technology module of the 2019 United States Annual Business Survey (ABS). The US ABS is a mandatory survey. It has been conducted annually since 2017, jointly by the US Census Bureau and the National Center for Science and Engineering Statistics within the National Science Foundation. Each year the survey incorporates new content based on emerging relevant topics.

Skills and Training: The section on Skills and Training asked about the importance of digital skills and other non-digital skills, and whether the organisation offers off- or on-the-job training for the adoption of the six aforementioned digital technologies. The digital skills are those defined in the European Digital Competence Framework for Citizens (DigComp). Other skills are integrated from multiple sources, which include the US Occupational Information Network (O*NET) system and the UK Employer Skills Survey (ESS). The O*NET is developed by the US Department of Labor's Employment and Training Administration. It describes occupations in terms of the knowledge, skills and abilities required, as well as the activities and tasks performed. The ESS is commissioned by the UK Department for Education. It has been conducted biennially across the four UK nations since 2011.

The ADiTS survey was implemented online by the Greater Manchester Chamber of Commerce (GMCC) from April to July 2022. It was launched on 4th April 2022 and disseminated to GMCC's network in Greater Manchester. The questionnaire was sent to approximately 2,800 member firms located mainly in Greater Manchester,[1] using a mass

[1] The survey was also distributed through the Alliance Manchester Business School (AMBS) Business Engagement, the Manchester Science Park and other organisations connected to AMBS and located

mailer approach. The survey closed in mid-July and achieved a total of 120 participants, representing a 4.3% response rate.

3.2 Measurement

This section presents the relevant variables from the ADiTS survey used in this report.

Adoption of digital technology

Firms were asked about their level of adoption of the six digital technologies, measured on a 5-point Likert scale: “did not use”, “tested, but did not use”, “low use”, “moderate use” and “high use”.

Motivations to adopt digital technologies

For the adoption of each digital technology, the survey asked firms about six motivations to adopt a particular digital technology, each measured by a binary variable that indicates “yes” or “no”. The motivations included “automation”, “upgrading outdated processes”, “improving process quality”, “product range expansion”, “adopting standards and accreditation”, and “consequences of the pandemic”.

Barriers to adopt digital technologies

Respondents were asked about the barriers to adopting each individual digital technology, also measured by binary variables, including ten factors: “technology is costly”, “technology is immature”, “lack of access to data”, “data are unreliable”, “lack of access to human capital”, “laws and regulations”, “safety and security concerns”, “lack of access to capital”, and “technology is not applicable”.

Impact of adopting digital technologies on firms’ productivity

Looking at the impact of technology adoption, we considered two aspects: productivity and employment. For the former aspect, the survey considered seven elements related to the consequences of digital technology adoption on a firm’s productivity, namely, “production costs/cost of processes”, “selling price”, “time to delivery”, “volume of production”, “product diversification”, “number of customers” and “types of customers”. The impact of adopting each digital technology on each of these aspects was measured using a 5-point Likert scale: “decreased considerably”, “decreased”, “did not change”, “increased” and “increased considerably”.

Impact of adopting digital technologies on employment

The second outcome we analysed was impact on employment. The same 5-point Likert scale used for the productivity questions was used to measure the impact of adopting digital technologies on employment, covering the following seven elements: “number of employees”, “skill level of employees”, “STEM skills of employees”, “number of production workers”,

in Greater Manchester. Firms that reported a postal code outside this region have been excluded from the analysis.

"number of non-production workers", "number of supervisory workers" and "number of non-supervisory workers". Definitions for the last four categories are provided in Appendix A.

Importance of skills

The next section of the questionnaire captured the relative importance of skills categorised into two groups: digital skills and other non-digital skills. Table 1 presents definitions of the key five digital and five non-digital skills included in the questionnaire which were used in this report.

Each of the ten categories of skills has multiple elements. The importance of each of the skill element was measured on a 5-point Likert scale: "not at all important", "somewhat important", "neither important nor unimportant", "somewhat important" and "very important". Using values from 1 to 5 to indicate the importance from low to high, we calculated the mean value for each of the ten categories of skills. Details of the elements of each skill are reported in Appendix B.

Table 2. Skills in the ADiTS survey

Digital skills	Non-digital skills
1a. Information and data literacy	2a. Basic and practical skills
1b. Communication and collaboration	2b. Social and soft skills
1c. Digital content creation	2c. Technical skills
1d. Safety	2d. System skills
1e. Problem solving	2e. Resource management skills

Training

The last section of the questionnaire captured training activities in relation to the adoption of each digital technology. The training questions covered three options: "off-the-job training", "on-the-job training" and "no training".

4. Results

This section presents the results of the ADiTS survey. It starts with the demographic information of the sample (4.1), and then moves on to the description of the adoption of digital technologies (4.2), including motivations for adoption (4.3), barriers to adopt (4.4), and impact (4.5), as well as the importance of skills and training (4.6). Finally, the last section presents some highlights for specific sectors (4.7).

4.1. Sample respondents' characteristics

The majority of the respondents were companies (88%) as opposed to public-sector organisations (3%) or charities (7%). Of the respondents, 82% came from the service sector, within which they mostly are defined as knowledge-intensive services (KIS)[2] (66%). Although the manufacturing sector represents only 9% of the respondents, most of them (73%) are from high or medium-tech firms. Small and Medium Enterprises (SMEs) represented more than 70% of the respondents. Specifically, more than one-third of respondents were micro firms (with fewer than 10 full-time employees (FTE); more than a quarter had between 10 and 49 employees; less than a quarter of them were medium-sized, that is with a number of employees between 50 and 249; and 7% employed more than 250 people.

Table 3. Key demographics of respondents

Demographic variable		% respondents	
Organisation type	Private sector	88%	
	Public sector	3%	
	Other (charity, voluntary, NPO)	7%	
	Unknown	2%	
Industry type	Manufacturing	9%	
	High-Medium-tech		*73%*
	Low-tech		*27%*
	Services	82%	
	Knowledge-intensive (KIS)		*66%*
	Less knowledge-intensive (LKIS)		*31%*
	Services unspecified		*3%*
	Construction	3%	
	Electricity, gas and water supply	2%	
	Unknown	4%	
Firm size	1–9 FTE	35%	
	10–49 FTE	28%	
	50–99 FTE	11%	
	100–249 FTE	11%	
	≥ 250 FTE	7%	
	Unknown	8%	
Total (N=120)		100%	

[2] For the classification of industry type, we use the definition of high-medium technology manufacturing industries and knowledge-intensive services from Eurostat, "High-tech industry and knowledge-intensive services: Annex 3", that takes into consideration NACE Rev.2. More information is available here.

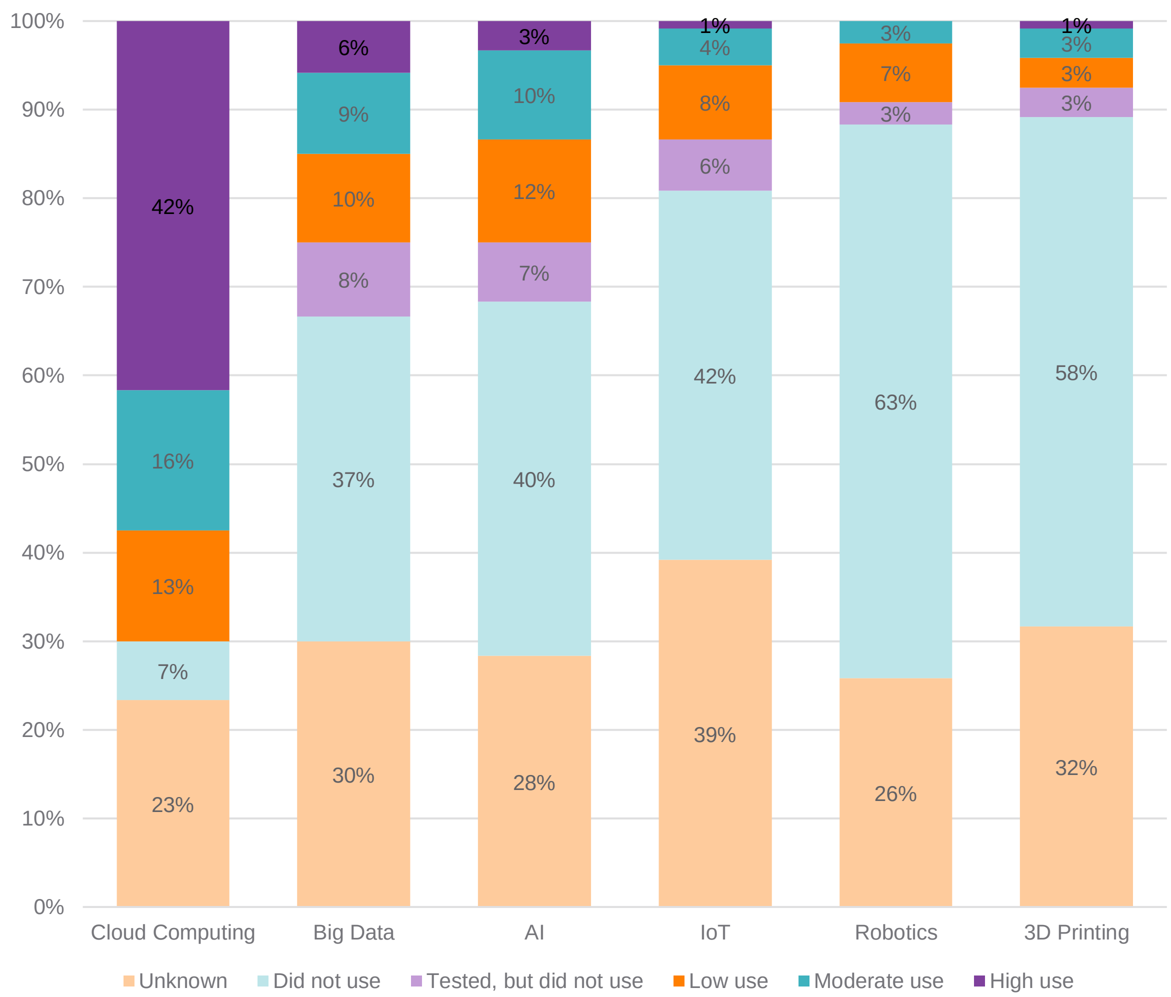
Source: Authors' own elaboration based on ADiTS survey

Looking at the innovation activities of the firms, 38% of the respondents indicated that they invested in R&D, with most of the surveyed organisations reporting engagement in process innovations (81%) and more than half reporting engagement in product (goods and/or service) innovation (62%).

4.2 Adoption of advanced digital technologies

The first part of the study concerns the adoption of digital technologies. We define DT adopters as the respondents that reported "high use", "moderate use" or "low use" to at least one of the six specific technologies, and non-adopters as those for whom all technologies were reported as either "did not use" or "tested, but did not use". For the purpose of comparing the importance of skills between DT adopters and non-adopters (Section 4.6 and Section 4.7), we included the "unknown" responders in non-adopters.

Figure 1. Adoption of digital technologies (% respondents)



Source: Authors' own elaboration based on ADiTS survey

Out of the 120 respondents, 78% adopted at least one of the six DTs listed, a quarter adopted two of them and 18% adopted three or more. Companies adopting Cloud Computing typically also adopted Big Data (11%) or AI (8%), making these the two most common combinations observed in the sample. Meanwhile, 3% reported that they did not use any of these technologies, and for 18% of respondents their adoption status could not be identified for all DTs.

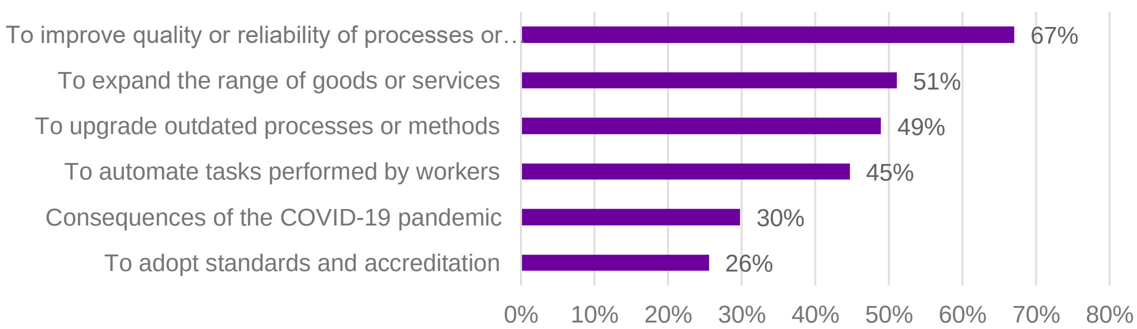
For each technology, the survey asked about the level of usage (high, moderate, low, tested but not used, not used). In Figure 1, the six digital technologies are analysed according to the level of usage (from most to least used).

Among the six digital technologies of interest, Cloud Computing was the most widespread, with adopters and non-adopters accounting respectively for 70% and 7% of the respondents, and with 42% respondents reporting high use of the technology. All other technologies were substantially less adopted in comparison. The distributions of adoption of Big Data and AI were similar: a quarter of the organisations reported using them, and 45% or more reported not using either technology. IoT, by comparison, was relatively less used – only 13% of respondents had adopted it and nearly half had not. It is interesting to note that, except for Cloud Computing, adopters mainly reported low use of these digital technologies. 3D Printing and Robotics were used by only about 10% of the respondents, while most of the participants (more than 60%) indicated that they had not adopted these two technologies.

4.3 Motivations to adopt digital technologies

We asked adopters of specific digital technologies about their motivations for adopting them. The results (Figure 2) indicate that *processor method quality improvement* was the most common reason, which was selected by two-thirds of the adopters of any of the six technologies. *Product or service range expansion* was the second most common motivation, with about half respondents ticking that box. This was followed by *processor method upgrade*, which motivated almost half of the adopters. *Task automation*, which in the literature is often associated with the adoption of digital technologies (mainly around industrial robots), was selected by 45% of the adopters. Questions about motivations to adopt referred to the last three years (2019–2021), so a specific motivation related to the COVID-19 pandemic was included in the questionnaire. Not surprisingly, 30% of the adoptions of digital technologies were encouraged by the *consequences of the pandemic*. This percentage is moderately higher than that of *compliance purposes*, which was selected by about a quarter of the adopters.

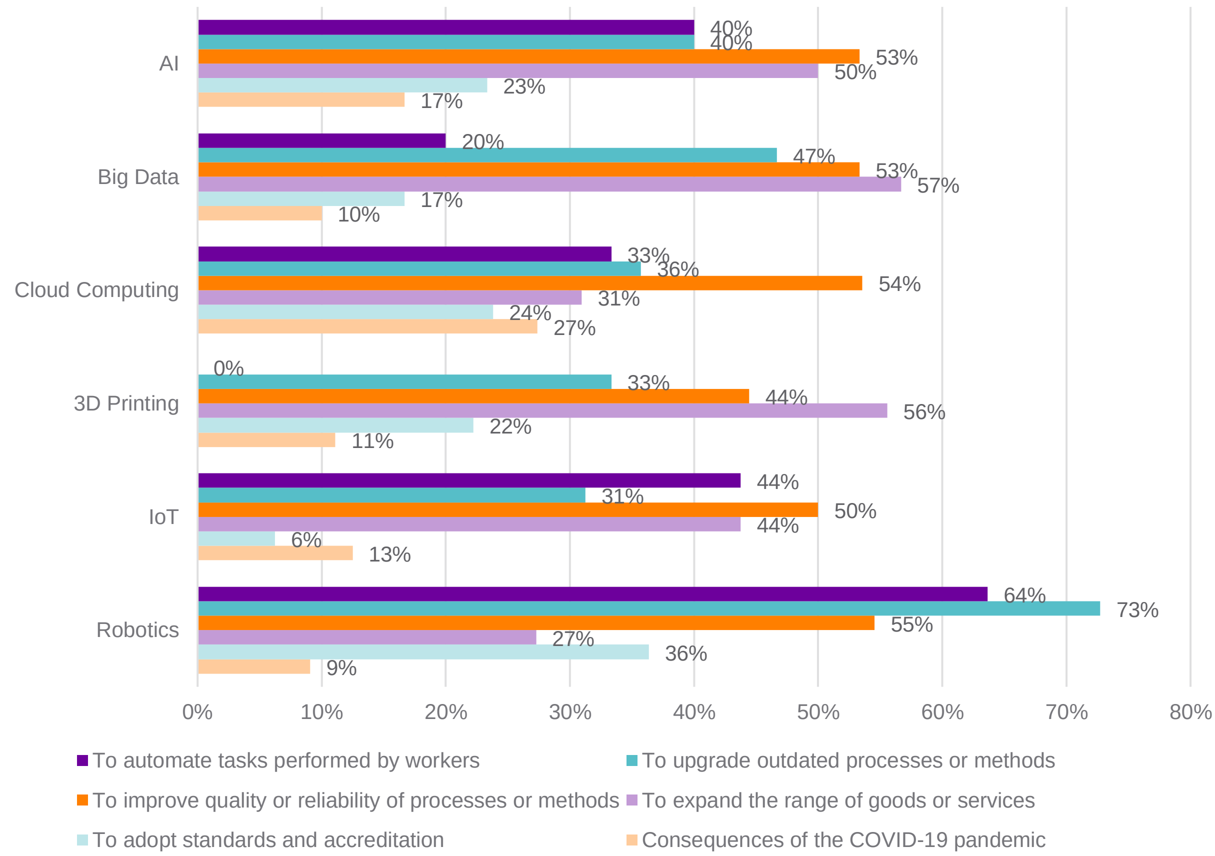
Figure 2. **Motivations to adopt digital technologies (% digital technology adopters)**



Source: Authors' own elaboration based on ADiTS survey

The importance of these factors shows some variation across the technologies (**Error! Not a valid bookmark self-reference.**). For AI adoption, *processor method quality improvement* was the most selected motivation (53%) and was chosen by a marginally greater percentage of the adopters compared to *product/service range expansion* (50%). This is the opposite of the motivations for using Big Data, where the latter was the most common (57%), followed by the former (53%). *Processor method quality improvement* was, again, the most common reason for the adoption of Cloud Computing, and was chosen by a considerably higher proportion of the adopters (54%) compared to other factors (36% or lower). *Processor method quality improvement* (50%) was also the most common reason for the adoption of IoT, followed by *automation and product range expansion* (44%). 3D Printing was adopted mostly for *expanding product range* (56%) and to *improve the quality and reliability of processes* (44%). Overall, the *adoption of standards/accreditations* and the *COVID-19 pandemic* were the least selected motivations for adopting 3D Printing. Motivations to adopt Robotics differed from other digital technologies. Robotics were most likely to be adopted to *upgrade processes or methods* (73%), for *automation* (64%) and to *improve quality and reliability of processes* (55%).

Figure 3. Motivations to adopt each type of digital technologies (% adopters of corresponding technologies)

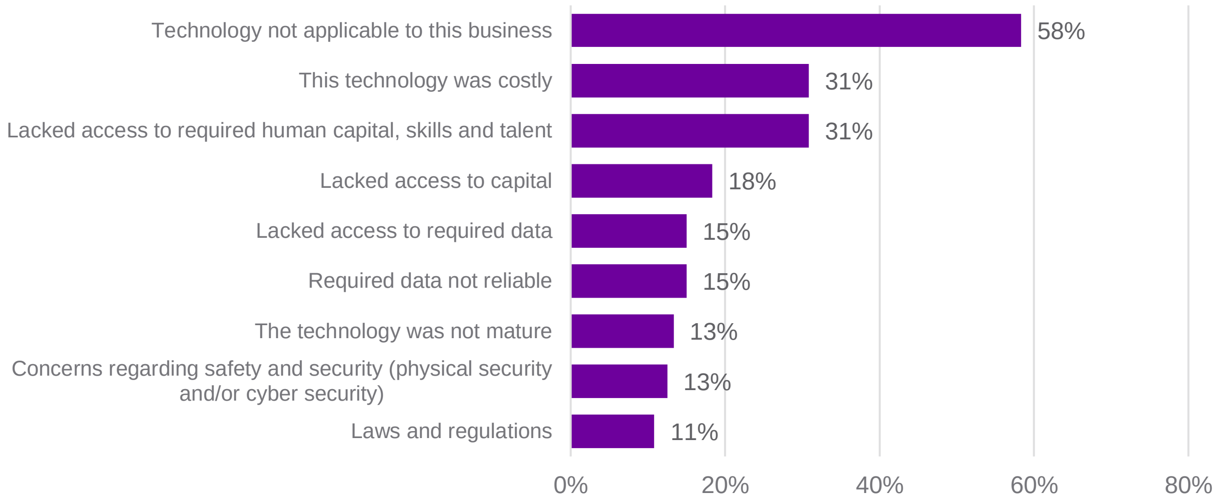


Source: Authors' own elaboration based on ADiTS survey

4.4 Barriers to adopting digital technologies

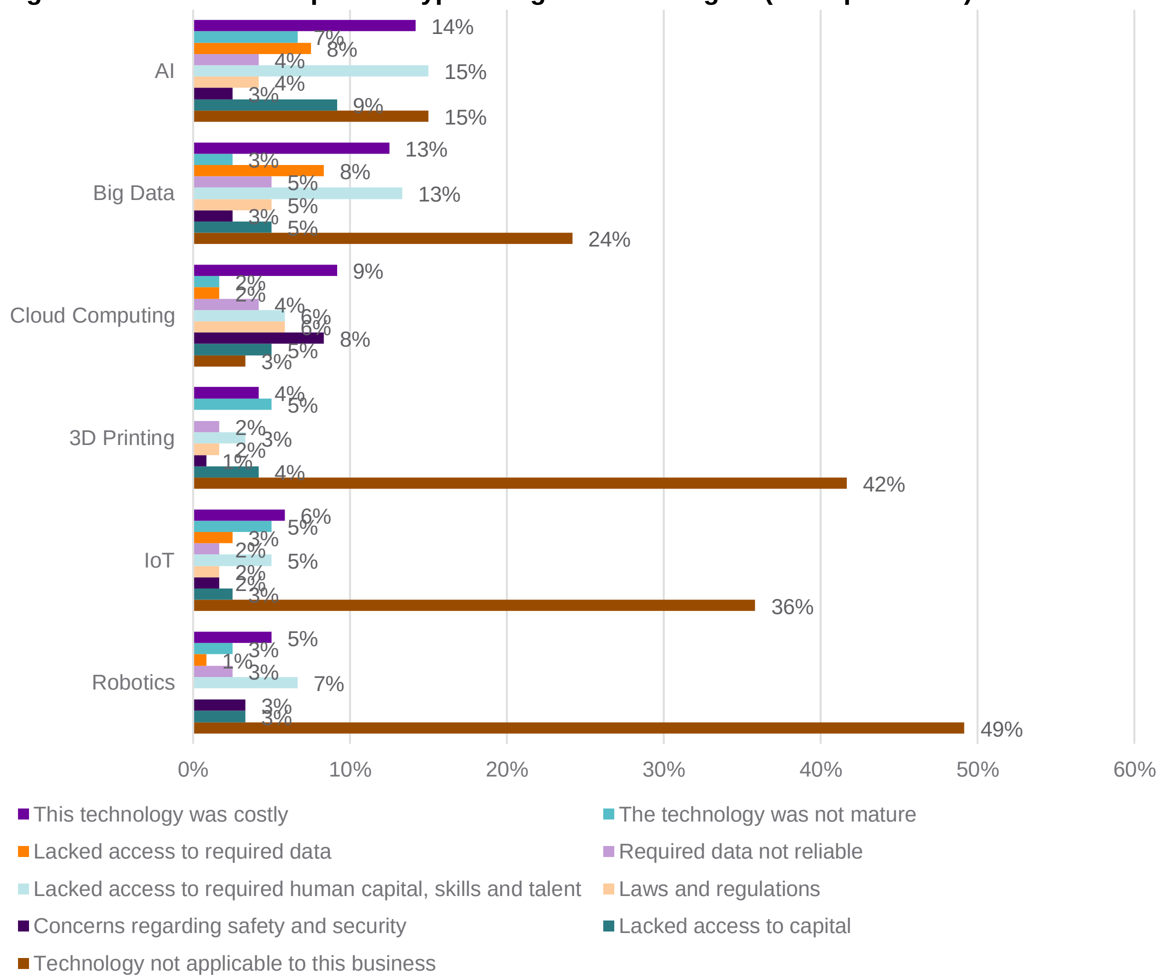
We asked respondents to indicate the factors which adversely affected their adoption of each of the digital technologies.

Figure 4. Barriers to adopt digital technologies (% respondents)



Source: Authors' own elaboration based on ADiTS survey

Figure 5. Barriers to adopt each type of digital technologies (% respondents)



Source: Authors' own elaboration based on ADiTS survey

As reported in Figure 4, more than half (58%) of the respondents reported at least one DT as being not applicable to them. This was most likely to be attributed to Robotics, 3D Printing and IoT, for which 49%, 42% and 36% of the respondents reported “not applicable”; in contrast, Cloud Computing had the most widespread applicability (with only 3% indicating “not applicable”), followed by AI (15%) and Big Data (24%). Amongst the various barriers listed, *cost* and *lack of human capital* were the most frequently selected. They affected almost one-third of the respondents who adopted one or more of the DTs listed.

More specifically, as shown in Figure 5, AI and Big Data were the most cost-sensitive technologies (respectively 14% and 13% respondent reported cost as a barrier to adoption). By comparison, only 3D Printing (4%), Robotics (5%) and IoT (6%) reported *cost* as am impediment to adoption, which is not surprising given that these technologies are typically not applicable to their businesses. *Lack of access to human capital*, *skills and talent* is also likely to constraint AI (15%) and Big Data (13%). In contrast, it was reported less frequently as an obstacle for adopting 3D Printing (3%), IoT (5%) or Robotics (7%).

Cloud Computing was adopted by 70% of respondents, and less than 10% of the firms reported any barriers to using this technology. *Costs* and *Safety and security concerns* were barriers to adoption for respectively 9% and 8% of the respondents. It should be noted that none of them indicated that Cloud Computing was not applicable to them.

4.5 Impact of digital technologies on firms’ outputs

Respondents were asked about the impact of the adopted DTs in two dimensions: employment and productivity. Table 4 and Table 5 report the percentages of firms that declared increases or decreases in those two dimensions. Firms could select from five categories to describe the impact of adoption of digital technologies on employment and productivity: 5 – “increased considerably”, 4 – “increased”, 3 – “did not change”, 2 – “decreased” and 1 – “decreased considerably”, for each particular statement. To present the effect of adopting a specific type of digital technologies we classify 1 and 2 as “decrease” (▼), and 4 and 5 as “increase” (▲). The percentages for “any DT” are based on the average impact of all the technologies adopted by a respondent: a factor of employment or productivity is considered “decreased” for the adopter if the average impact is between 1 and 3, and is considered “increased” if the average is between 4 and 5. Those that selected “did not change” are not reported in the tables.

In respect of employment, adopters of digital technologies were most likely to find a positive impact on overall *skills levels* and the *level of Science, Technology, Engineering and Mathematics (STEM) skills*, with 41% and 27% of the adopters of digital technologies improving in these two aspects. These effects were particularly widespread among the adopters of Robotics (91% and 73% respectively), AI (53% and 47%) and Big Data (47% and 47% respectively). While such effects were relatively less common among the adopters of 3D Printing (33% and 22% respectively), compared to the adopters of other technologies, 3D Printing adopters were more likely to have an increase in their *number of workers* (56%) in general, without particular skills needs. Nearly half (48%) of the adopters of Cloud Computing experienced an increase in the *level of skills*. However, a relatively lower percentage (26%) of these adopters reported an increase in STEM skills, compared to the adopters of most other technologies. By comparison, IoT adopters were more likely to increase their STEM skills (44%) than overall skill levels (38%).

More than one-fifth of the adopters of digital technologies (22%) reported an increase in the *number of workers* overall. Looking at the individual technologies, the highest increases of workers were found for adopters of 3D Printing (56%), AI (40%) and Robotics (36%). At the same time, respondents who adopted Robotics also reported the highest decreases in number of workers (27%), followed by IoT (25%); this reduction affected mainly non-production workers (18%) in the former, and both production and non-production workers in the latter (19%). In addition, adopting 3D Printing negatively affected the number of non-production workers and of workers with no supervisory roles (both of which decreased for 22% of adopters).

Table 4. Impact of adopting digital technologies on employment (% adopters where the factor increased or decreased)

	Any DT		AI		Big Data		Cloud Computing		3D Printing		IoT		Robotics	
	▲	▼	▲	▼	▲	▼	▲	▼	▲	▼	▲	▼	▲	▼
Skill levels of workers	41%	1%	53%	7%	47%	3%	48%	1%	33%	22%	38%	6%	91%	0%
STEM skills of workers	27%	2%	47%	10%	47%	3%	26%	4%	22%	11%	44%	6%	73%	0%
Number of workers	22%	11%	40%	13%	20%	3%	30%	7%	56%	11%	25%	25%	36%	27%
Number of production/manual workers	14%	6%	27%	10%	7%	0%	14%	4%	33%	0%	19%	6%	45%	18%
Number of non-production (clerical/white collar) workers	11%	6%	30%	17%	3%	0%	15%	4%	22%	22%	19%	19%	18%	18%
Number of workers with supervisory roles (managers and executives)	10%	6%	30%	10%	0%	0%	11%	4%	22%	11%	25%	6%	45%	9%
Number of workers with no supervisory roles (including both production and non-production)	13%	6%	33%	13%	3%	0%	13%	2%	22%	22%	19%	19%	45%	9%
N	94		30		30		84		9		16		11	

Source: Authors' own elaboration based on ADiTS survey

The effect on productivity was measured by multiple indicators in the survey (Table 5). The *number of customers* and *product diversification* were increased for almost two-fifths (39%) and a third (32%) of the adopters of DTs, respectively. In addition, 17% of adopters reported a decrease in *production costs/cost of the process*, which was marginally lower than the proportion of adopters for whom the costs increased (19%). Similar results were observed with respect to *time to delivery* – adopting digital technologies caused the time to delivery to decrease for one-fifth of the adopters, and to increase for a slightly larger proportion of them (22%).

Nevertheless, the impact could vary between specific technologies. Adopting Cloud Computing, Big Data or AI was most likely to increase the *number of customers* (43%, 40% and 37% respectively). In contrast, adopting Robotics increased the *volume of production* for most of its adopters (82%); and increased *product diversification* for more than two-fifths of them (45%). Considerable proportions of 3D Printing adopters also enhanced their *volume of production* or *product diversification* (both 56%). In addition, more than two-fifths (44%) of 3D Printing adopters and nearly two-fifths (38%) of IoT adopters increased their *types of customers*. Notably, typically a higher proportion of the adopters of a specific type of technology increased their *production costs/cost of process* and *time to delivery,* compared to the percentage of the adopters where the corresponding factor of productivity was decreased. However, for Robotics, the proportion of "increased" (27% and 36% respectively for the aforementioned factors) was not necessarily higher than the proportion of "decreased" (36% and 36% respectively).

Table 5. Impact of adopting digital technologies on productivity (% adopters where the factor increased or decreased)

	Any DT		AI		Big Data		Cloud Computing		3D Printing		IoT		Robotics	
	▲	▼	▲	▼	▲	▼	▲	▼	▲	▼	▲	▼	▲	▼
Production costs/cost of processes	19%	17%	17%	13%	10%	7%	23%	12%	44%	22%	25%	6%	27%	36%
Selling price of goods and/or service	17%	3%	33%	3%	17%	7%	25%	2%	33%	0%	25%	0%	36%	9%
Time to delivery	22%	20%	27%	23%	13%	17%	29%	15%	22%	11%	31%	19%	36%	36%
Volume of production	23%	1%	33%	3%	23%	3%	24%	0%	56%	0%	31%	6%	82%	0%
Product diversification	32%	3%	33%	3%	30%	0%	38%	4%	56%	0%	25%	13%	45%	0%
Number of customers	39%	6%	37%	7%	40%	0%	43%	6%	33%	0%	31%	6%	9%	27%
Types of customers	30%	5%	33%	10%	30%	0%	32%	6%	44%	0%	38%	13%	18%	9%
N	94		30		30		84		9		16		11	

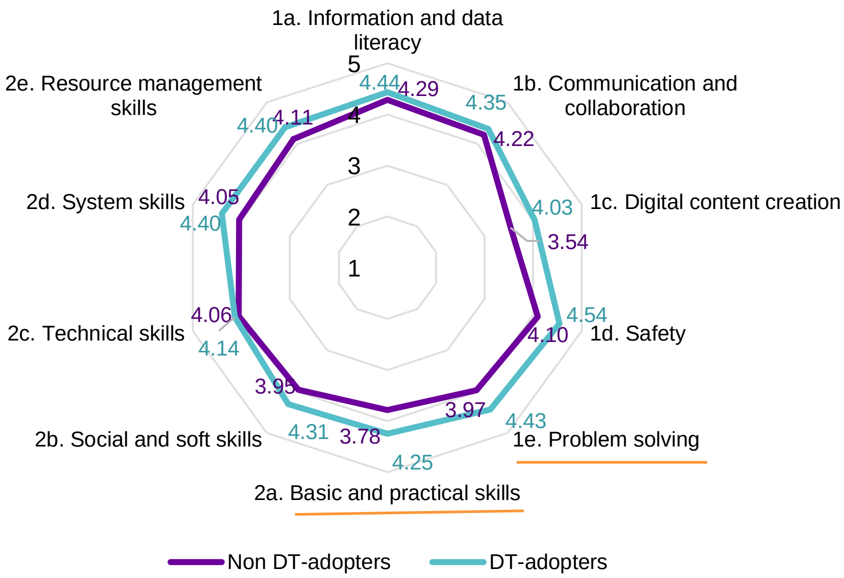
Source: Authors' own elaboration based on ADiTS survey

4.6 Digital skills and other non-digital skills

An important factor in the adoption of digital technologies is whether there are specific (digital and non-digital) skill needs associated with their adoption. **Error! Reference source not found.** compares the importance given to a set of skills by adopters and non-adopters of DTs. The figure reports the means on a scale of 1 to 5. Underlined skills are significantly different between adopters and non-adopters based on *t*-test comparison (see Appendix C for further information).

Figure 6 reveals that adopters on average rated “problem-solving skills” and “basic and practical skills” statistically significantly more highly than non-adopters (based on the results of *t*-tests). Because there were no significant differences between the two groups, and considering the limited number of non-adopter respondents in the survey, we focus on the importance of skills for those firms that adopted advanced digital technologies. Results show that among the digital skills (i.e., skills numbered as 1x), the adopters of DTs considered “safety” to be the most important skill (4.54). Results from the Analysis of Variance (ANOVA) and post-hoc analysis based on the Turkey HSD approach help to compare the significant differences between the means reported by adopters (see Table 6). They indicate that “safety”, “information and data literacy” and “problem solving” are significantly more important than “digital content creation”. Among non-digital skills (i.e., those numbered as 2x), “system skills” and “resource management skills” were given the highest score on average (4.40), albeit none of them was found to be significantly different from the rest of the skills.

Figure 6. Importance of digital and non-digital skills for adopters and non-adopters of digital technologies



Source: Authors’ own elaboration based on ADiTS survey

Table 6. Comparisons among skills for adopters of digital technologies

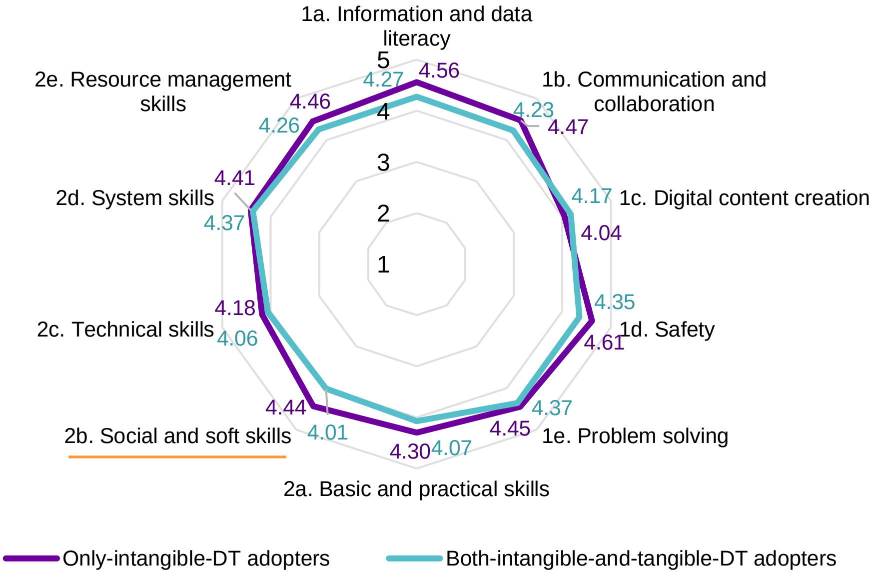
A	B	Mean Difference (A–B)	Std. Error	Sig.
Information and data literacy (4.44)	Digital content creation (4.03)	0.4079*	0.1196	0.024
Digital content creation (4.03)	Safety (4.54)	–0.5135*	0.1203	0.001
	Problem solving (4.43)	–0.3971*	0.1215	0.037
Safety (4.54)	Technical skills (4.14)	0.4009*	0.1187	0.026

Note: Only significant results reported.
Source: Authors’ own elaboration based on ADiTS survey

We also compared the importance of specific skills for adopters of “intangible” DTs and adopters of both “intangible” and “tangible” DTs. “Intangible” DTs include AI, Big Data and

Cloud Computing, and “tangible” DTs refer to 3D Printing, Internet of Things and Robotics – such categorisation is based on the DTs’ typical forms of application as well as their “homogeneity” as detected in the previous descriptive statistics. As shown in **Error! Reference source not found.**, the adopters of only “intangible” valued “social and soft skills” significantly higher than the adopters of both tangible and intangible DTs.

Figure 7. Importance of digital and non-digital skills for adopters of “intangible” DTs and adopters of both “intangible” and “tangible” DTs



Source: Authors’ own elaboration based on ADiTS survey

Figure 8 reports the skills importance per type of technology. The comparisons between the adopters and non-adopters of individual technologies did not find any statistically significant difference in the importance of skills associated with the adoption of AI (Chart A), Big Data (Chart B), or 3D Printing (Chart D). With respect to the other technologies, “safety”, “basic and practical skills” and “social and soft skills” were more important to the adopters of Cloud Computing than non-adopters (Chart C). Interestingly, “information and data literacy” and “social and soft skills” were significantly more important to non-adopters of IoT than to adopters (Chart E). The adopters of Robotics rated all skills lower than their non-adopter counterparts, with significant differences in six skills out of ten: “information and data literacy”, “communication and collaboration”, “safety”, “problem solving”, “social and soft skills” and “resource management skills” (Chart F).

Regarding specific technologies, the ANOVA results did not find the importance of skills to be significantly different among the adopters of corresponding technologies, except for Cloud Computing (note that almost 90% of the DT adopters adopted Cloud Computing) (Table 7). Similarly to what was found for the average digital-adopters, “safety” received the highest score of importance (4.56) for the adopters of Cloud Computing; “safety” as well as “information and data literacy” were significantly more important than “digital content creation” to these adopters.

Figure 8. Importance of digital and non-digital skills per type of technology

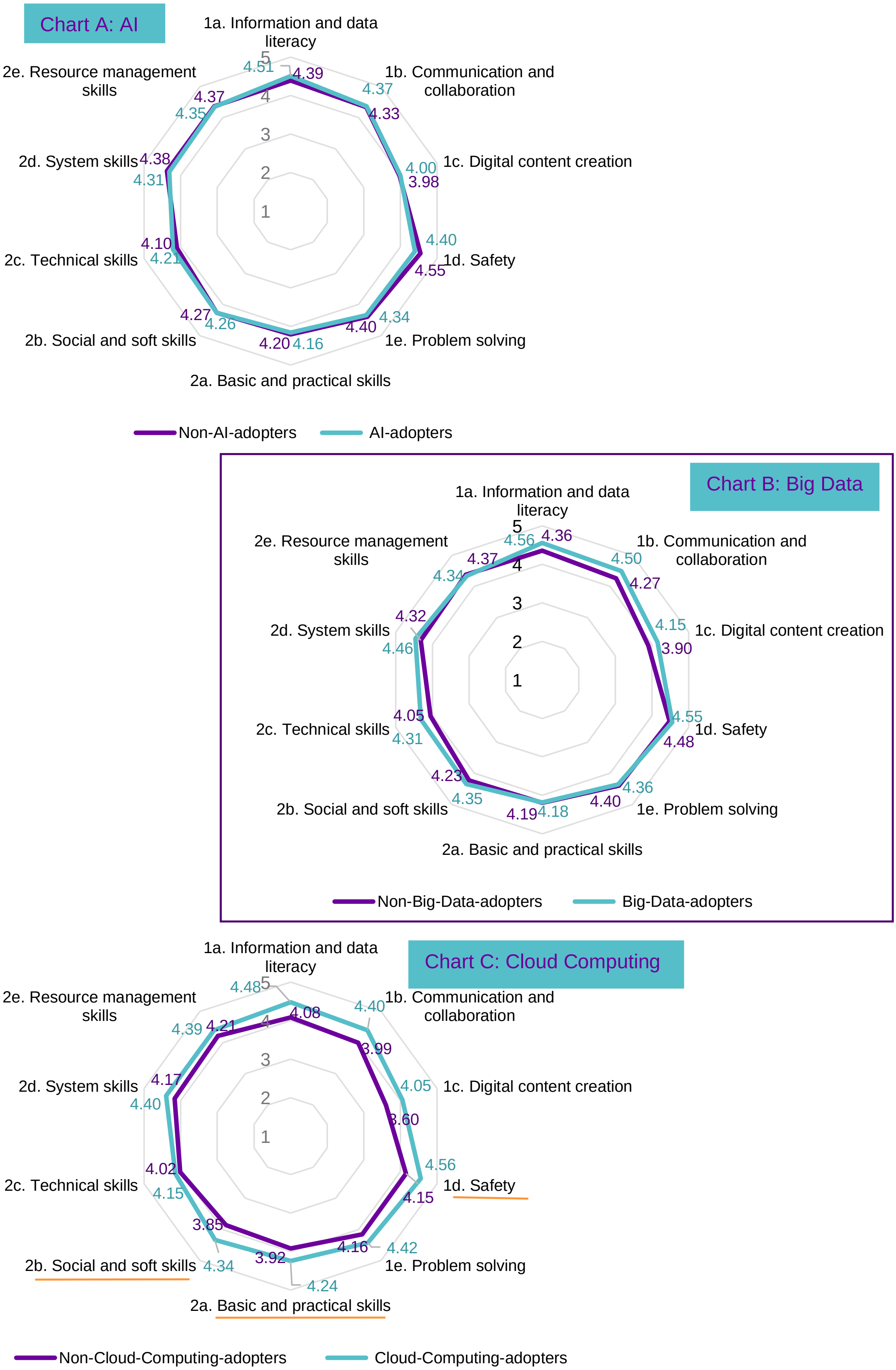
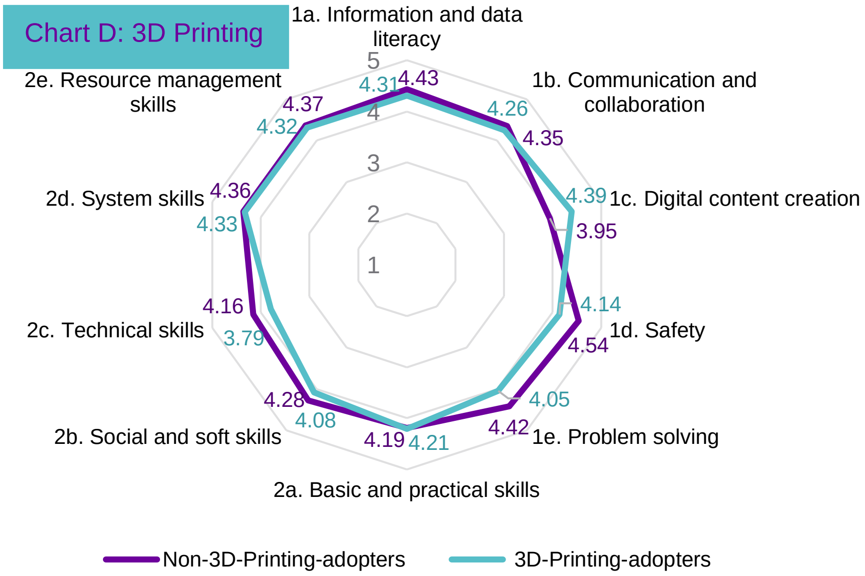
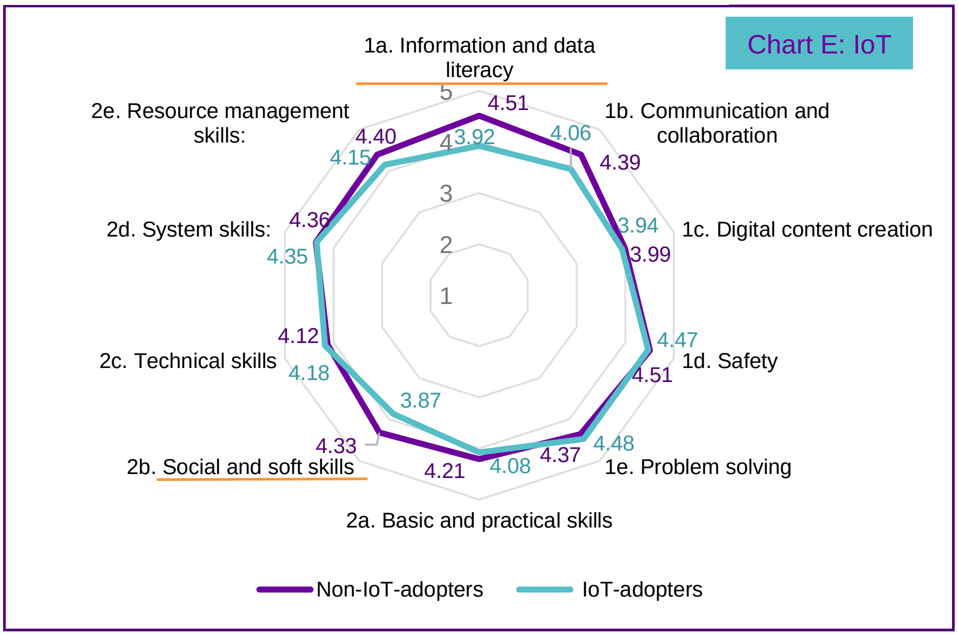


Figure 8 (continued). Importance of digital and non-digital skills per type of technology





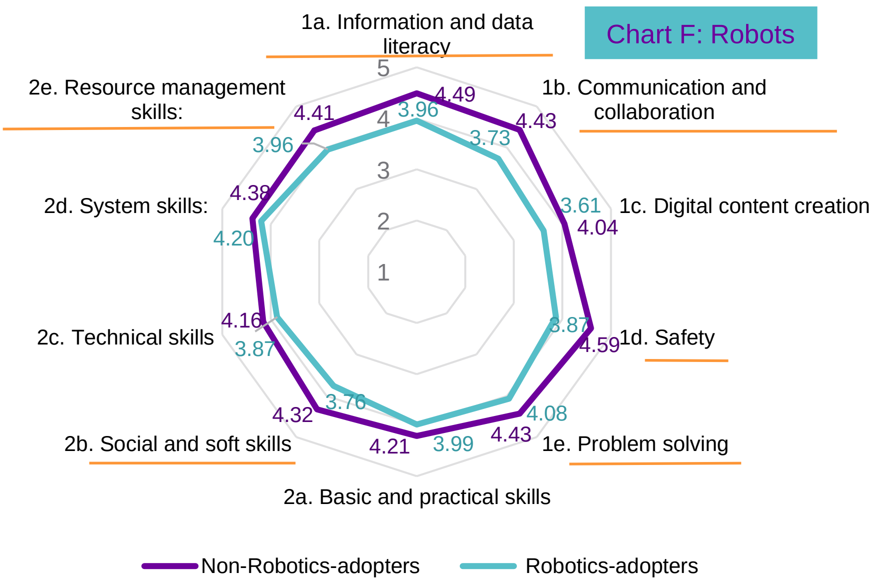


Table 7. Comparisons among skills for adopters of Cloud Computing

A	B	Mean Difference (A–B)	Std. Error	Sig.
Information and data literacy (4.48)	Digital content creation (4.05)	0.4261*	0.1184	0.013
Digital content creation (4.05)	Safety (4.56)	–0.5052*	0.1188	0.001
Safety (4.56)	Technical skills (4.15)	0.4060*	0.1163	0.018

Note: Only significant results reported.
Source: Authors' own elaboration based on ADiTS survey

The survey asked about training related to the adoption of the individual DTs. Nearly half of the respondents did not provide valid information on training. One-third of the respondents organised training for the adoption of at least one of the DTs. By contrast, one-fifth of them did not organise any training. The most frequently organised training was reported by companies adopting Cloud Computing. Training was less frequently arranged by the adopters of Robotics, 3D Printing and IoT.

Table 8. Training related to the adoption of digital technologies

	Any DT	AI	Big Data	Cloud Computing	3D Printing	IoT	Robotics
Organised	33%	13%	14%	26%	5%	7%	7%
On the job		*8%*	*11%*	*22%*	*3%*	*4%*	*5%*
Off the job		*4%*	*3%*	*4%*	*2%*	*3%*	*2%*
Not organised	20%	39%	40%	28%	47%	47%	49%
Unknown	48%	48%	46%	46%	48%	47%	44%
Total (N=120)	100%	100%	100%	100%	100%	100%	100%

Source: Authors' own elaboration based on ADiTS survey

4.7 Sectoral highlights

This section focuses on the comparison between different types of sectors, based on Eurostat's classification of manufacturing and service industries by technological and knowledge intensity. Due to the small number of observations in manufacturing industries in the sample, we combine high- and medium-technology manufacturing sectors with knowledge-intensive services (KIS). The report first provides results for the high-medium-tech manufacturing sectors and KIS sectors together (hereafter "KI-HT") compared to "Other sectors". The KI-HT group includes manufacturing firms in the pharmaceutical area, computers and electronics, as well as services in scientific research and development, information and communication, water/air transport, finance and insurance, legal and accounting services, management consultancy, architecture and engineering, advertising and market research, employment, education, human health and social work, arts, entertainment and recreation.

The results present comparisons between both KI-HT and other sectors when possible, but due to the sample size of the latter, some of the figures are only presented for KI-HT. Second, the analysis focuses only on the service sector highlighting some differences between KIS and LKIS (less knowledge-intensive services), as the majority of our survey respondents came from this sector. Services such as wholesale and retail trade, accommodation and food, postal and courier services, real estate, rental and leasing, travel agency, office administration and support, and repair of motor vehicles/computers/personal and household goods are classified as LKIS.

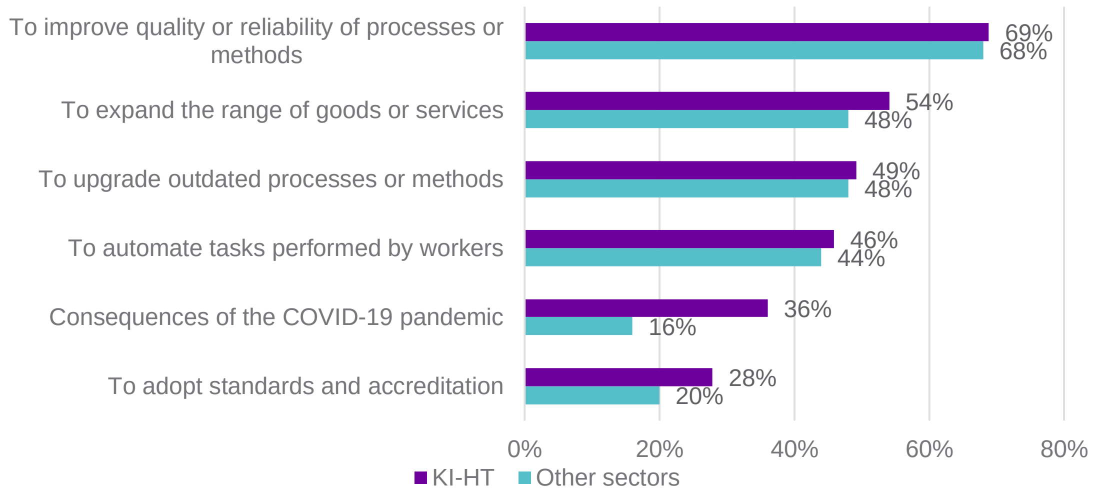
4.7.1 KI-HT sectors versus Other sectors

There were 73 and 33 respondents in the sample that can be identified as operating in KI-HT sectors and Other sectors respectively. Among the KI-HT organisations, 84% adopted at least one of the DTs. In terms of specific technologies, three-quarters of KI-HT organisations used Cloud Computing, followed by Big Data (30%) and AI (26%); IoT adopters accounted for 16% of adopters; and less than 10% used Robotics (8%) or 3D Printing (7%). By comparison, a relatively lower percentage of the respondents from Other sectors (76%) were adopters of digital technologies. Cloud Computing (70%) was, again, the most commonly adopted technology in these sectors, far more frequently than the second most adopted technology, AI (21%), the third most used, Big Data (18%); IoT (9%), Robotics (9%) and 3D Printing (6%) were used by less than 10% of the KI-HT respondents. Overall, KI-HT sectors had higher adoption rates, but their counterparts in Other sectors did not lag too much.

Error! Reference source not found.9 reports the motivations for adopting digital technologies ranked by their importance. Improving *quality or reliability process or methods* was selected by 69% and 68% of firms in KI-HT and Other sectors respectively, followed by *expansion of goods and services* (54% and 48%). Less than 50% of the firms in both groups reported *upgrading process/methods* and *automation* as motivations to adopt DTs. The highest difference in the answers related to the *effect of the pandemic*, where the adoption of DTs in KI-HT sectors, compared to their counterparts, was mostly driven by the consequences of the pandemic (36% and 16% respectively). This suggests that exogenous events, i.e., changes in the business environment, tended to have stronger influence on firms in the KI-HT sectors than on their counterparts in Other sectors with regard to adopting digital technologies, possibly because the KI-HT sectors are more capable of responding to changes with technological approaches.

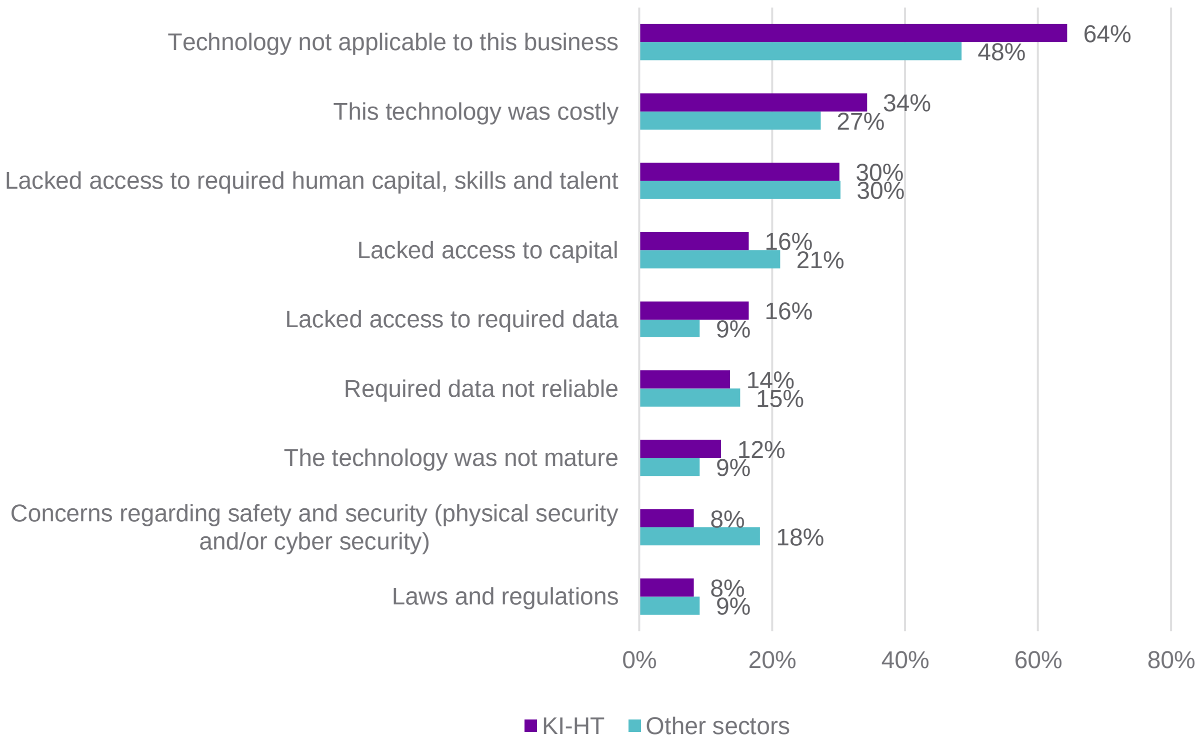
On the other hand, the adoption of DTs in KI-HT sectors also appears to have been hindered by *applicability* (64%) and *costs* (34%) while these same categories were selected by fewer firms in Other sectors (48% and 27% respectively). Notably, firms in both sectors reported *lack of access to required human capital, skills and talent* as the third main reason for not adopting digital technologies (30%). There were a few barriers that hindered technology adoption in Other sectors more than in KI-HT ones: *lack of access to capital* (21%), *data not reliable* (15%) and *concerns regarding security* (18%).

Figure 9. Motivations for adopting digital technologies for KI-HT and Other sectors (% DT adopters)



Source: Authors' own elaboration based on ADiTS survey

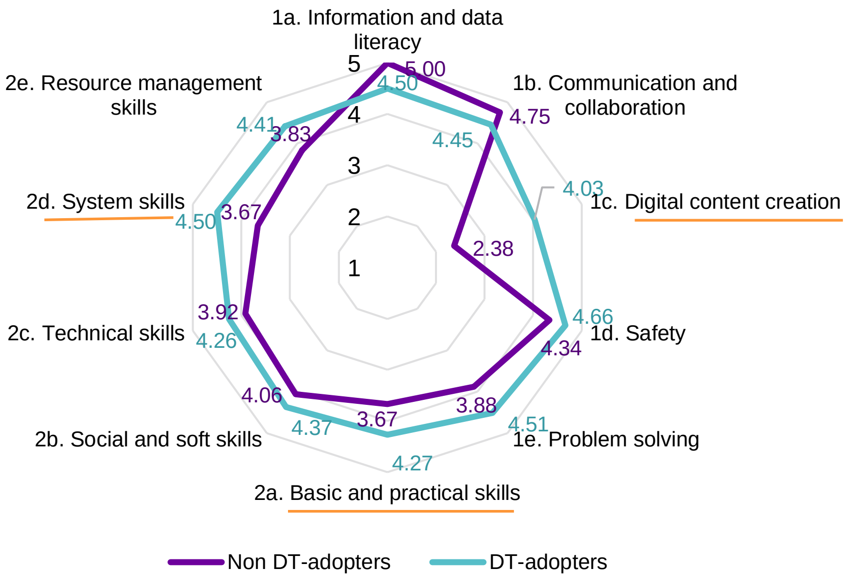
Figure 10. Barriers to adopting digital technologies for KI-HT and Other sectors (% respondents)



Source: Authors' own elaboration based on ADiTS survey

Finally, we look at the importance of skills in KI-HT sectors (Figure 11). Due to data availability, it is not possible to report the equivalent information for Other sectors. In general, KI-HT adopters of digital technologies tended to rate higher both digital and non-digital skills, except for "information and data literacy" and "communication and collaboration". However, key skills for adopters were "digital content creation" (4.03), "basic and practical skills" (4.27) and "system skills" (4.5), as the importance given to these specific skills by adopters was significantly higher compared to non-adopters.

Figure 11. Importance of digital and non-digital skills by technology adoption in KI-HT sectors



Source: Authors' own elaboration based on ADiTS survey

4.7.2 KIS versus LKIS sectors

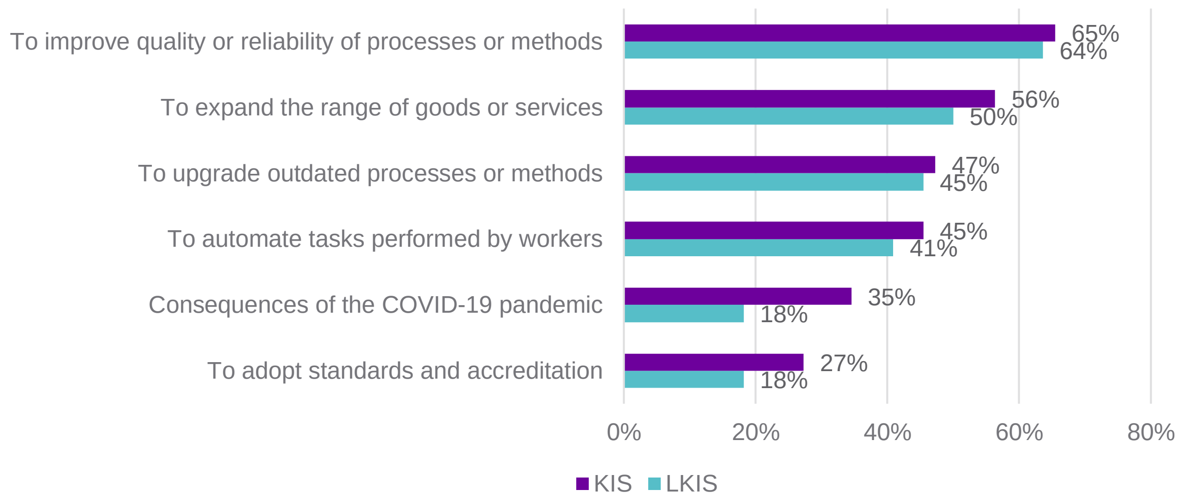
There were 65 and 33 organisations in the sample classified as operating in KIS sectors and LKIS sectors[3] respectively. Among the KIS organisations, 85% adopted at least one of the digital technologies. Specifically, more than three-quarters (78%) of the KIS organisations used Cloud Computing, followed by Big Data (31%) and AI (26%); IoT adopters accounted for 15% of adopters; and very few used 3D Printing (6%) or Robotics (5%). By comparison, a relatively lower percentage of the respondents from LKIS sectors (67%) adopted any of the DTs. Cloud Computing (61%) was, again, the most adopted technology, ahead of the second and third most adopted technologies, AI (18%) and Big Data (15%). IoT (9%), Robotics (6%) and 3D Printing (6%) were used by only a few organisations in this group.

Figure 12 shows the motivations for adopting digital technologies ranked by their importance. The relative importance of the six motivations was the same for KIS and LKIS organisations, and most of the motivations were almost equally likely to be selected by the two groups of adopters. *Improving quality or reliability process or methods* was the most frequently selected motivation (selected by 65% and 64% of KIS and LKIS adopters respectively), followed by *expanding product (goods or services) range* (56% and 50% respectively). Between 40–50% of the adopters in both groups reported *upgrading process or methods* (47% and 45% respectively for KIS and LKIS) or *automation* (45% and 41% respectively for KIS and LKIS) as a motivation. The greatest difference between the two groups came from the *impact of the pandemic*, where the adoption of DTs in KIS sectors, compared to their counterparts in LKIS sectors, was more likely to be driven by the consequences of the pandemic (35% versus 18%).

[3] There were thirty organisations identified as LKIS. Three service firms which did not report a specific sub-sector have been included in this category.

There was also a relatively large difference between KIS and LKIS organisations in terms of *compliance* – compared to their counterparts in LKIS sectors, those in KIS sectors were more likely to be influenced by standards and accreditations (27% vs.18%).

Figure 12. Motivations for adopting digital technologies for KIS and LKIS organisations (% DT adopters)

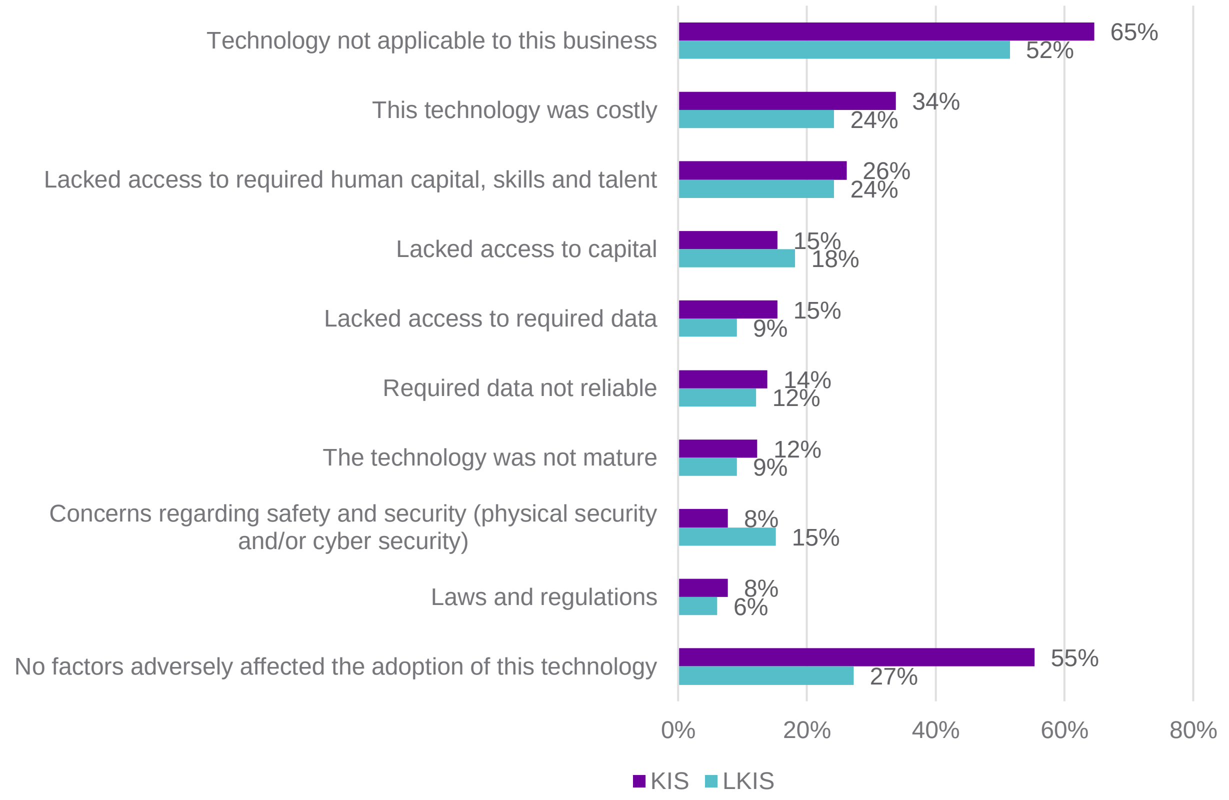


Source: Authors' own elaboration based on ADiTS survey

Figure *13* indicates that, among the barriers listed, the adoption of DTs in KIS organisations was most likely to be hindered by *applicability* (65%) and *costs* (34%). The same applies to LKIS organisations, albeit those barriers were selected by relatively smaller percentages of LKIS respondents (52% and 24% respectively). Notably, both groups reported the *lack of access to required human capital, skills and talent* as the third greatest barrier to adopting the DTs. The corresponding share of respondents was only marginally higher in KIS organisations (26%) than in LKIS ones (24%). This indicates that the lack of relevant human resources impeded the adoption of digital technologies in service sectors. In KIS organisations, *safety and securing* (8%) was less of a barrier than *capital* (15%), *data access* (15%), *data reliability* (14%) or *technology maturity* (12%), while in LKIS organisations, *safety* (15%) was less likely to hamper the adoption of digital technologies than *capital* (18%), and more likely than the other three barriers (9%, 12% and 9% respectively).

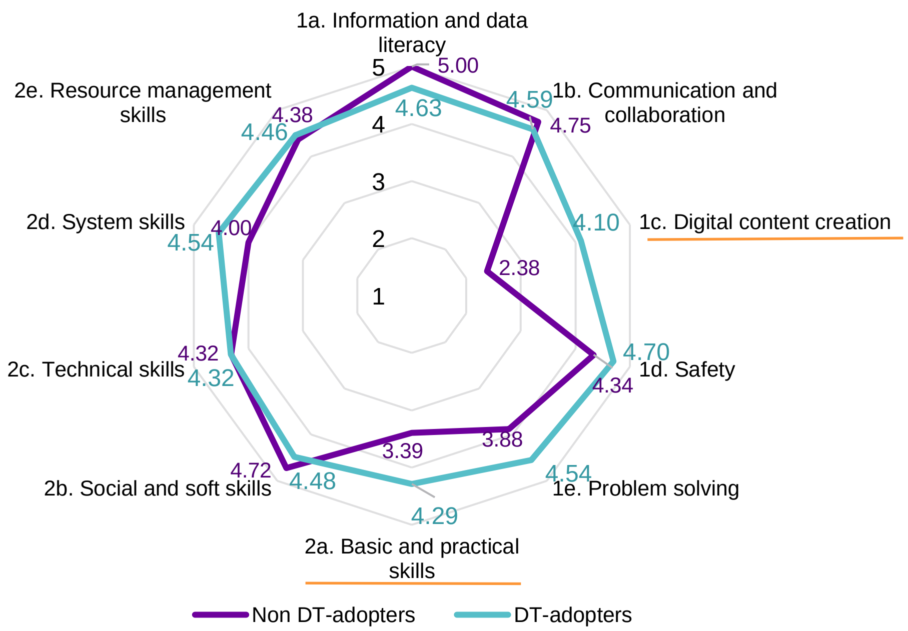
Figure *14* illustrates the importance of skills for adopters and non-adopters of digital technologies in KIS organisations. It shows that "digital content creation" (4.10) and "basic and practical skills" (4.29) were significantly more important to DT adopters than to non-adopters.

Figure 13. Barriers to adopt digital technologies for KIS and LKIS (% respondents)



Source: Authors' own elaboration based on ADiTS survey

Figure 14. Importance of digital and non-digital skills by technology adoption in KIS



Source: Authors' own elaboration based on ADiTS survey

5. Discussion and implications

The ADiTS survey provides evidence on recent patterns of technology diffusion and the pervasiveness of advanced digital technologies across firms and sectors in Greater Manchester. Some studies have referred to these six digital technologies (AI, Big Data, Cloud Computing, 3D Printing, IoT and Robotics) as "next generation digital technologies" because of their capacity to enable a business and economic revolution (Cho, et al., 2022). The Local Industrial Strategy of the Greater Manchester region is seizing opportunities from the potential for digital transformation to create better quality, future-facing jobs in all sectors of the economy. Digital technologies and digital skills are key elements of this transformation, and this study helps identify the set of firms leading the race to adopt technology.

Our results show that the adoption rate is 78%, meaning that approximately three out of four firms have adopted at least one type of advanced digital technology. This adoption rate is significantly higher than the 6.6% aggregate adoption rate for all AI-related technologies in the US (Zolas et al., 2020), 42% for the EU (Kazakova et al., 2020) and 57% in emerging economies (Chui et al., 2021), and there are several reasons for the differences. First, the US study, based on the American Businesses Census run by the National Statistical Office, uses a large-scale representative survey of US firms with a sample design which allows them to extrapolate results across the full business population. The other two reports are based on AI-specific surveys, while our study covers a wider range of advanced technologies. Adoption of DTs is mainly led by firms in the high-tech manufacturing sector and KIS sector. It is interesting to note that most of the sample respondents in this study are from the services sector (82%), including two-thirds classified as KIS. Historically, professional services, some of which are indeed KIS, have been considered a "vanguard sector" in the adoption of ICT (Barras, 1990), at the frontier of the adoption of new technology, and since the 1970s ICTs have been considered a key element of the service-based technological revolution (Brynjolfsson and McAfee, 2014). Contrary to the results in the US study, which finds that the largest and oldest firms tend to adopt more digital technologies (Zolas et al., 2020), our survey mainly documents the diffusion of digital technologies among SMEs. This result reflects the specific industrial context of the Greater Manchester city-region, which is made up predominantly of SMEs, and where the financial and other professional services sectors have acted as the engine of job growth for over a decade (BEIS, 2019).

Our study reveals that different DTs are at different states of diffusion. When we zoom in on the adoption rates per type of technology, our survey reports notable differences in the diffusion of advanced digital technologies. First, Cloud Computing is the most widespread technology, with 70% of firms reporting adopting it. This result is in line with the data presented for US firms, where Cloud Computing is adopted by different business functions within firms (Zolas et al., 2020). A possible explanation for this result is that the US firms in Zolas et al.'s study are much larger than those which participated in our study, and therefore when they adopt this networking technology, they do so to support multiple functions and processes; on the other hand, less resourceful small firms can take advantage of Cloud services as they can substitute for costly in-house computing capabilities with outsourced IT services (Jin and McElheran, 2017). While scaling up has traditionally been an advantage for large firms adopting new technologies, benefitting from economies of scale and larger returns on investment, more agile small firms might be able to quickly scale up using cost saving, and enjoying efficiencies resulting from the adoption of the latest Cloud Computing technologies

(Zolas et al., 2020). We conclude that Cloud Computing can be considered to be at an advanced stage of diffusion.

Most notably, we find that, except for Cloud Computing, the adoption of advanced digital technologies appears to be quite low overall (only occurring in one out of four firms), suggesting that firms are still experimenting with how these technologies can be implemented for their business, and are waiting for lower prices, clearer standards and, above all, the availability of skilled workers to support the adoption. Big Data and AI are the second most adopted technologies (25%). The figure for AI adopters is in line with those reported for micro-sized (21%) and small enterprises (22%) in Europe (Kazakova et al., 2020). These results suggest the importance of bundling data and intangibles (Haskel and Westlake, 2017) for adopters of digital technologies rather than a dependence on technologies related to the computerisation of industrial sectors (which is more the case for manufacturing firms). We can conclude here that non-Cloud Computing technologies are at an earlier stage of technology diffusion due to the low proportion of adopters and because the proportion of testing/low use of the technology is higher compared to that of high/medium use.

Next, we turn to discussing technology complementarities. It is important to note that the adoption of digital technologies does not tend to occur in isolation (Ciarli et al., 2021; Cho et al., 2022), and the adoption of one type of technology is often accompanied by the adoption of other types of DT to fully benefit from the complementarities resulting from their joint use, thus enabling companies to enjoy higher returns on their investment in these technologies. In this study, 43% of the firms that adopted DTs reported adopting two or more of them. In particular, 25% of respondents reported adopting two technologies at the same time, which is in line with the results presented by the European study mentioned earlier (Kazakova et al., 2020). The most frequent combinations of technologies are Cloud Computing and AI, and Cloud Computing and Big Data, reinforcing the importance of data and other intangibles. For example, firms wanting to use AI require large datasets to train their algorithms, which can be generated and collected at scale using Big Data practices, and processed and stored on Cloud Computing services (OECD, 2019).

The adoption of (not only digital) technologies is often related to different types of innovation and associated with changes in productivity and efficiency. According to our respondents, the main reason to adopt digital technologies is related to innovating processes, that is, to improving the quality or reliability of processes or methods (67%). This result is in line with the European survey which concludes that service-operations optimisation is the most common business function in which AI is introduced (Kazakova et al., 2020). Next, product innovation through the diversification of the portfolio of products and services was selected as a reason by half of the respondents. These motivations appear to be common across all types of DT, with the exception of Robotics, which reflects the composition of our sample.

Interestingly, while the literature has traditionally focused on the technology-employment duality (Bessen, 2018; Acemoglu and Restrepo, 2020; Klenert et al, 2020), only two-thirds of the firms in our study were motivated to adopt Robotics for the purpose of automating tasks currently performed by workers. Even in this case, the adoption of Robotics was mainly motivated by process innovation in relation to upgrading outdated process or methods. This resulting automation was mainly guided by KI-HT firms, suggesting that while earlier industrial Robotics adopters were mainly large establishments in the automotive sector, Robotics are now penetrating small- and medium-sized establishments in manufacturing (Leigh et al., 2022) and other sectors.

External exogenous events like the COVID-19 pandemic do not seem to accelerate particularly the diffusion of digital technologies, although KIS organisations have been particularly exposed as they are typically reliant upon extensive contact with clients, and working in teams on projects; during the pandemic they found their practices disrupted (Miles et al., 2021). According to Miles et al. (2021), the importance of new IT in KIS is a consequence of the COVID crisis, and firms have become more dependent on high-performance computing architectures and systems, high speed and wireless telecommunications, advanced information systems, etc. This could explain why 27% of the firms surveyed adopted Cloud Computing as a consequence of the pandemic.

The adoption of new technologies is understood to bring productivity gains, but it may be also associated with higher labour costs (for higher skilled workers), training and learning, and significant capital investment (Zolas et al., 2020). This is usually described as the "productivity paradox", because although these technologies hold great potential, there is limited evidence of aggregate productivity gains (Brynjolfsson et al., 2019). Innovation can drive productivity growth through technological change that reduces the cost or increases the volume of outputs, or both (Ugur and Vivarelli, 2021). In our study, the impact on productivity seems to have occurred in terms of the latter, as the percentage of firms reporting positive growth in volume of production/number of customers and product diversification/type of customers is higher compared to other options related to costs and prices. In fact, Robotics and 3D Printing technologies mainly affected the volume and diversification of products in the same way as traditional scaling-up effects in the manufacturing industry, while Cloud Computing, Big Data and AI allowed businesses to scale up through increasing their numbers of customers. At the same time, especially shortly after adopting new technologies, there can be substantial increases in production costs/cost of processes for technologies like Cloud Computing and 3D Printing that in turn increase the selling price of the goods and/or services.

An ongoing debate and key question in the literature is whether DTs will lead to prosperity or whether they will lead to mass joblessness and wage stagnation (Aghion et al., 2017). Overall, our results describe a positive scenario, in which 22% of adopters reported an increase in the number of employees in their firm. But the dilemma about the quality versus the quantity of workers remains. Digital technology adoption increases the necessary skill levels of workers, in particular for those adopting Robotics (91%), AI (53%), Cloud Computing (48%) and Big Data (47%). In this case, skills become a remarkably important intangible asset for firms and, indeed, the lack of access to the required human capital and skills is one of the main barriers that was reported to adopting digital technologies (as well as its cost): 31% of the firms reported these two barriers hampering technology diffusion, particularly in the case of AI and Big Data. This result is in line with those presented in other European countries where the difficulty of hiring new staff with the rights skills and the cost of adoption are the main internal obstacles to adopting AI (Kazakova et al., 2020).

A potential takeaway from this result is that the firms participating in our survey were still early adopters of the majority of the digital advanced technologies studied. While the cost of the technology seems to affect more KI-HT sectors, the lack of skills is a common problem regardless of sector. If skills are a key factor in the adoption of technology, training should be understood as a vehicle enabling an appropriate match between employers’ needs and employees’ capabilities. However, only one out of three firms had organised training activities in relation to the adoption of advanced technologies (particularly in relation to Cloud Computing). Among those that did it, tailored, specific on-the-job training was the most frequent option. This raises significant policy questions about the role that (higher) education providers could or should play to develop the right skill sets and offer flexible learning opportunities to re-skill and up-skill not only to the new generations of the workforce, but also through lifelong learning opportunities.

Indeed, looking at the skill needs for the adoption of DTs, some differences emerge. First, adopters of DTs tend to rank both digital and non-digital skills more highly, but key differences appear for capabilities related to problem solving (technical problems, identifying needs and technological responses, creativity, identifying competence gaps) in a digital environment, as well as for practical traditional skills like numeracy, literacy, IT, reading and writing. Second, our survey highlights that among the adopters of DTs, digital skills constitute a significant key asset, as they rank them higher, on average, than traditional basic skills. In particular, different elements of safety (protecting devices, personal data and privacy, health and wellbeing, as well as environmental) play a key role. It is also important to note that digital skills requirements are technology and sector specific. For example, safety is a key and relevant skill for Cloud Computing adopters, and digital content creation is a key element for DT adopters in the KI-HT sector.

6. Conclusions

Digital technologies often involve reconfiguring activities for the production of goods and services, as well as the characteristics of jobs and the types of skills that companies need. Nevertheless, we still know little about the extent of the adoption of DTs by businesses and therefore the impact on their activities, including their employment and skills needs. While adopting digital technologies requires companies to rethink their activities and processes, and workers to reconsider their ability to perform new tasks and jobs (i.e., up-skilling and re-skilling), paradoxically, little is known about the specific new skill requirements and changes in employment resulting from the development of DTs. Further, while aggregate statistics do not seem to suggest that adopting DTs is associated with productivity gains at the economy level, which is often the case for new technologies, there is little evidence on its impact on productivity at a firm level. Based on an original, fine-grained survey, the study contributes to understanding the extent to which firms adopt DTs, the types of skills associated with DTs, their motivations and constraints around adopting DTs, and the effect of adopting DTs on firms' employment and productivity.

We provide a first attempt to map and analyse the adoption of DTs and skills needs in Greater Manchester. First, our study offers a unique collection of data on the adoption of six different advanced digital technologies (AI, Big Data, Cloud Computing, 3D Printing, IoT and Robotics). Observing variation among firms in the adoption and use of technology is critical for understanding the underlying mechanisms at work. Only with a higher-resolution lens will it be possible to accurately characterise the broader effects of technology adoption on firms' outputs and processes. Second, in the most recent policy agenda, skills are included as one of the twelve missions to Level Up the UK where, "by 2030, the number of people successfully completing high-quality skills training will have significantly increased in every area of the UK" (HM Government, 2022). The present study contributes to this debate by identifying the skills lacking and needed for each DT, to guide policymakers to make choices and develop plans regarding into which technological sectors to specialise, and to support the development of specific skill sets. This study also provides insights for firms' managers to support their understanding of the right combination of DT investment and human capital skills requirements to reap the potential gains.

Looking towards the future, one important aspect that remains unclear is what come first, technologies or skills, i.e., whether firms require and/or develop certain skills once they have adopted DTs, or whether they first need to acquire those skills in order to adopt DTs in the first place. To put it differently, do companies not adopt DTs because they do not have digital skills in-house? Is the lack of digital skills a barrier to adopting DTs? Or do companies first adopt DTs and then address their skill needs by recruiting more workers with digital skills or developing these skills in-house (by up-skilling and re-skilling)? Our study suggests that at this early stage of adoption and diffusion of DTs, companies need and are waiting for a higher supply of skilled and talented workers, and they are quite reluctant to train them on the job. Policies aimed at supporting on-the-job training for digital skills could provide a much-needed boost to the adoption advanced digital technologies, while secondary and tertiary education institutions form the next generation of skilled workers for the digital transformation in the UK.

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Appendix A. Definitions

Artificial Intelligence (AI)

AI is a branch of computer science and engineering devoted to making machines intelligent. Intelligence is that quality that enables an entity to perceive, analyse, determine a response and act appropriately in its environment. Systems with artificial intelligence perform functions including, but not limited to, speech recognition, machine vision and machine learning.

- Speech recognition transforms human speech into a format useful for computer applications (for example, a digital assistant).
- Machine vision uses sensors and software that allow images to be used as an input for computer applications (for example, systems that sort or inspect objects or support navigation in mobile equipment).
- Machine learning uses statistical software and data to "learn" and make better predictions without reprogramming (for example, recommender systems for websites, or sales and demand forecasting).

AI technologies also include virtual agents, deep learning platforms, decision management systems, biometrics, text analytics, and natural language generation and processing.

Cloud-Based Computing Systems and Applications

Cloud systems and applications are computing resources available on-demand via the internet. Cloud Computing enables ubiquitous, convenient, on-demand internet access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction.

Robotics

Robotic equipment (or robots) comprises automatically controlled, reprogrammable and multipurpose machines used in automated operations in industrial and service environments. Robots may be mobile, incorporated into standalone stations or integrated into a production line. A robot may be part of a manufacturing cell or incorporated into another piece of equipment.

Industrial robots may perform operations such as palletising, pick and place, machine tending, material handling, dispensing, welding, packing/repacking and cleanroom.

Service robots are commonly used in businesses for such operations as cleaning, delivery, construction, inspection, and medical services such as dispensing or surgery.

Internet of Things (IoT)

IoT encompasses devices with self-identification capabilities (localisation, status diagnosis, data acquisition, processing and implementation) that are connected via standard communication protocols. IoT technologies are used in manufacturing applications, and in many others industries (housing and construction, automotive sector, environment, smart city, agriculture, health, etc.).

3D Printing

3D Printing (also known as Additive Manufacturing) finds its application in the prototyping (to support the product development process, static simulation and wind tunnels, etc.), manufacturing (direct production of products), maintenance, repair and modelling phases.

3D Printing/Additive manufacturing includes the following seven categories: Binder Jetting, Directed Energy Deposition, Material Extrusion, Material Jetting, Powder Bed Fusion, Sheet Lamination and Photo Polymerisation.

Big Data

Big Data includes methods and tools to process large volumes of data for manufacturing, supply chain management and maintenance. The data can come from IoT systems connected to the productive layer (for example, with sensors and associated equipment), or the exchange between IT systems for production and warehouse management. Specific applications in this area are machine learning tools for planning and forecasting, predictive maintenance and simulation.

Production worker

A worker (up through the line supervisor level) engaged in activities or processes that result in the creation of products, goods or services. This includes those directly engaged in fabricating, processing, assembling, inspecting, receiving, storing, handling, packing, warehousing, shipping (but not delivering), maintenance, repair, janitorial and guard services, product development, auxiliary production for the own use of business (e.g., a power plant), record keeping and other services closely associated with these production operations in the business covered by the report. Employees above the working-supervisor level are excluded.

This group includes the following employees in the construction sector: working supervisors, qualified craft employees, mechanics, apprentices, helpers, labourers and so forth, engaged in new work, alterations, demolition, repair, maintenance and the like, whether working at the site of construction or in shops or yards at jobs (such as pre-cutting and preassembling) ordinarily performed by members of the construction trades.

Non-production worker

A worker engaged in the following activities: supervision above the working foreman level, sales (including driver-salesman), sales delivery (highway truck drivers and their helpers), advertising, credit collection, installation and servicing of own products, clerical and routine office functions, executives, purchasing, financing, legal, professional and technical activities. Also included are employees on the payroll of the business engaged in the construction of major additions or alterations to the plant who are utilised as a separate workforce.

Supervisory worker

A worker whose major responsibility is to supervise, plan or direct the work of others, such as those in top executive and managerial positions, officers of corporations, department heads and superintendents.

Non-supervisory worker

A worker who does not supervise, plan or direct the work of others. This group includes employees (not above the working-supervisor level) such as office and clerical employees, repairers, salespersons, operators, drivers, physicians, lawyers, accountants, nurses, social employees, research aides, teachers, drafters, photographers, beauticians, musicians, restaurant employees, custodial employees, attendants, line installers and repairers, labourers, janitors, guards and other employees at similar occupational levels whose services are closely associated with those of the employees listed.

Appendix B. Digital and non-digital skills

1. **Digital skills**

1a. Information and data literacy

1a.1. Browsing, searching and filtering data, information and digital content: to articulate information needs to search for data and information in digital environments.
1a.2. Evaluating data, information and digital content: to analyse, compare and critically evaluate the credibility and reliability of digital sources.
1a.3. Managing data, information and digital content: to organise, store and retrieve data and information in digital environments.

1b. Communication and collaboration

1b.1. Interacting through digital technologies: to interact through different digital technologies and understand digital communication.
1b.2. Sharing through digital technologies: to share data and information with others trough digital technologies
1b.3. Engaging in citizenship through digital technologies: to participate in society through digital services.
1b.4. Collaborating through digital technologies: to use digital tools and technologies for collaborative processes and co-creation.
1b.5. Netiquette: to be aware of behavioural norms and know-how while using digital environments.
1b.6. Managing digital identity: to create and manage digital identities while protecting one's own reputation.

1c. Digital content creation

1c.1. Developing digital content: to create and edit digital content in different formats.
1c.2. Integrating and re-elaborating digital content: to modify, refine, improve and integrate information and content.
1c.3. Copyright and licences: to understand how copyright and licenses apply to digital content.
1c.4. Programming: to plan and develop a sequence of understandable instructions for a computing system.

1d. Safety

1d.1. Protecting devices: to protect devices and digital content understanding risks and threats.
1d.2. Protecting personal data and privacy: to protect personal data and privacy in digital environments.
1d.3. Protecting health and wellbeing: to be able to avoid health risks and threats to physical and psychological wellbeing using digital technologies.
1d.4. Protecting the environment.

1e. Problem solving

1e.1. Solving technical problems: to identify technical problems when operating devices and using digital environments and to solve them.
1e.2. Identifying needs and technological responses: to assess needs and identify, evaluate, select and use digital tools to solve them.
1e.3. Creatively using digital technologies: to use digital tools and technologies to create knowledge and to innovate processes and products.
1e.4. Identifying digital competence gaps: to understand where one's own digital competence needs to be improved or updated.

2. **Non-digital skills**
    - **2a. Basic and practical skills:** developed capacities that facilitate learning or the more rapid acquisition of knowledge, such as:
        - 2a.1. Basic numerical skills and understanding
        - 2a.2. Communication in a foreign language
        - 2a.3. Computer literacy/basic IT skills
        - 2a.4. Manual dexterity – e.g., to mend, repair, assemble, construct
        - 2a.5. Reading and understanding instructions, guidelines, manuals or reports
        - 2a.6. Writing instructions, guidelines, manuals or reports

    - **2b. Social and soft skills:** developed capacities used to work with people to achieve goals, such as:
        - 2b.1. Analytical thinking
        - 2b.2. Customer handling skills
        - 2b.3. Flexible thinking
        - 2b.4. Instructing, teaching or training people
        - 2b.5. Making speeches or presentations
        - 2b.6. Managing their own feelings, or handling feelings of others
        - 2b.7. Networking
        - 2b.8. Persuading or influencing others
        - 2b.9. Sales skills
        - 2b.10. Strategic thinking
        - 2b.11. Team working

    - **2c. Technical skills:** developed capacities used to design, set-up, operate, and correct malfunctions involving application of machines or technological systems, such as:
        - 2c.1. Achievement focus
        - 2c.2. Adapting to new equipment or materials
        - 2c.3. Advanced numerical or statistical skills
        - 2c.4. Advanced or specialists IT skills
        - 2c.5. Complex problem-solving skills
        - 2c.6. Drafting skills
        - 2c.7. Processing advanced knowledge of products and services offered by their organisation
        - 2c.8. Specialist skills or knowledge needed to perform the role

    - **2d. System skills:** developed capacities used to understand, monitor, and improve socio-technical systems, such as:
        - 2d.1. Judgment and decision making
        - 2d.2. Systems analysis and evaluation

    - **2e. Resource management skills**: developed capacities used to allocate resources efficiently, such as:
        - 2e.1. Management of financial and material resources
        - 2e.2. Management of personnel resources
        - 2e.3. Strategic thinking and networking
        - 2e.4. Time management

Appendix C. Summary tables

Table C.1 Adoption of digital technologies – % respondents

	Cloud Computing	**Big Data**	**AI**	**IoT**	**Robot**	**3D Printing**
High use	42%	6%	3%	1%	0%	1%
Moderate use	16%	9%	10%	4%	3%	3%
Low use	13%	10%	12%	8%	7%	3%
Tested, but did not use	0%	8%	7%	6%	3%	3%
Did not use	7%	37%	40%	42%	63%	58%
Unknown	23%	30%	28%	39%	26%	32%
Total (N=120)	100%	100%	100%	100%	100%	100%

Table C.2 Motivations for adopting digital technologies – % DT adopters

	Yes	No	Total (N=94)
To improve quality or reliability of processes or methods	67%	33%	100%
To expand the range of goods or services	51%	49%	100%
To upgrade outdated processes or methods	49%	51%	100%
To automate tasks performed by workers	45%	55%	100%
Consequences of the COVID-19 pandemic	30%	70%	100%
To adopt standards and accreditation	26%	74%	100%

Table C.3 Motivations for adopting each type of digital technologies – % adopters of each DT

	3D Printing	Robotics	IoT	Cloud Computing	Big Data	AI
To automate tasks performed by workers	0%	64%	44%	33%	20%	40%
To upgrade outdated processes or methods	33%	73%	31%	36%	47%	40%
To improve quality or reliability of processes or methods	44%	55%	50%	54%	53%	53%
To expand the range of goods or services	56%	27%	44%	31%	57%	50%
To adopt standards and accreditation	22%	36%	6%	24%	17%	23%
Consequences of the COVID-19 pandemic	11%	9%	13%	27%	10%	17%
N	9	11	16	84	30	30

Table C.4 Barriers to adopting digital technologies – % respondents

	Yes	No	Total (N=120)
Technology not applicable to this business	56%	42%	100%
Technology was costly	31%	69%	100%
Lacked access to required human capital, skills and talent	31%	69%	100%
Lacked access to capital	18%	82%	100%
Lacked access to required data	15%	85%	100%
Required data not reliable	15%	85%	100%
Technology was not mature	13%	87%	100%
Concerns regarding safety and security (physical security and/or cybersecurity)	13%	88%	100%
Laws and regulations	11%	89%	100%

Table C.5 Barriers to adopting each type of digital technology – % respondents

	3D Printing	Robotics	IoT	Cloud Computing	Big Data	AI
Technology was costly	4%	5%	6%	9%	13%	14%
Technology was not mature	5%	3%	5%	2%	3%	7%
Lacked access to required data	0%	1%	3%	2%	8%	8%
Required data not reliable	2%	3%	2%	4%	5%	4%
Lacked access to required human capital, skills and talent	3%	7%	5%	6%	13%	15%
Laws and regulations	2%	0%	2%	6%	5%	4%
Concerns regarding safety and security (physical security and/or cybersecurity)	1%	3%	2%	8%	3%	3%
Lacked access to capital	4%	3%	3%	5%	5%	9%
Technology not applicable to this business	42%	49%	36%	3%	24%	15%
N	120	120	120	120	120	120

Table C.6 Importance of digital and non-digital skills: comparison between adopters and non-adopters

		Non DT-adopters	DT-adopters	*t*-test
Digital skills		4.02	4.34	–1.20
Other skills		3.91	4.29	–2.00
Digital skills	1a. Information and data literacy	4.29	4.44	–0.50
	1b. Communication and collaboration	4.22	4.35	–0.40
	1c. Digital content creation	3.54	4.03	–1.15
	1d. Safety	4.10	4.54	–1.65
	1e. Problem solving	3.97	4.43	–1.75*
Other skills	2a. Basic and practical skills	3.78	4.25	–2.40**
	2b. Social and soft skills	3.95	4.31	–1.50
	2c. Technical skills	4.06	4.14	–0.30
	2d. System skills	4.05	4.40	–1.50
	2e. Resource management skills	4.11	4.40	–1.30

		Non-AI-adopters	AI-adopters	*t*-test
Digital skills		4.32	4.31	0.05
Other skills		4.22	4.28	–0.35
Digital skills	1a. Information and data literacy	4.39	4.51	–0.60
	1b. Communication and collaboration	4.33	4.37	–0.15
	1c. Digital content creation	3.98	4.00	–0.10
	1d. Safety	4.55	4.40	0.90
	1e. Problem solving	4.40	4.34	0.40
Other skills	2a. Basic and practical skills	4.20	4.16	0.30
	2b. Social and soft skills	4.27	4.26	0.00
	2c. Technical skills	4.10	4.21	–0.55
	2d. System skills	4.38	4.31	0.35
	2e. Resource management skills	4.37	4.35	0.10

		Non-Big-Data-adopters	Big-Data-adopters	*t*-test
Digital skills		4.27	4.42	–0.95
Other skills		4.21	4.32	–0.80
Digital skills	1a. Information and data literacy	4.36	4.56	–1.10
	1b. Communication and collaboration	4.27	4.50	–1.20
	1c. Digital content creation	3.90	4.15	–0.95
	1d. Safety	4.48	4.55	–0.45
	1e. Problem solving	4.40	4.36	0.25
Other skills	2a. Basic and practical skills	4.19	4.18	0.05
	2b. Social and soft skills	4.23	4.35	–0.70
	2c. Technical skills	4.05	4.31	–1.40
	2d. System skills	4.32	4.46	–0.85
	2e. Resource management skills	4.37	4.34	0.20

		Non-Cloud-Computing-adopters	Cloud-Computing-adopters	*t*-test
Digital skills		3.93	4.38	–2.15**
Other skills		3.93	4.30	–2.25**
Digital skills	1a. Information and data literacy	4.08	4.48	–1.60
	1b. Communication and collaboration	3.99	4.40	–1.60
	1c. Digital content creation	3.60	4.05	–1.35
	1d. Safety	4.15	4.56	–1.85*
	1e. Problem solving	4.16	4.42	–1.20
Other skills	2a. Basic and practical skills	3.92	4.24	–1.90*
	2b. Social and soft skills	3.85	4.34	–2.45**
	2c. Technical skills	4.02	4.15	–0.55
	2d. System skills	4.17	4.40	–1.10
	2e. Resource management skills	4.21	4.39	–0.95

		Non-IoT-adopters	IoT-adopters	*t*-test
Digital skills		4.35	4.11	1.15
Other skills		4.27	4.07	1.10
Digital skills	1a. Information and data literacy	4.51	3.92	2.55**
	1b. Communication and collaboration	4.39	4.06	1.35
	1c. Digital content creation	3.99	3.94	0.20
	1d. Safety	4.51	4.47	0.15
	1e. Problem solving	4.37	4.48	-0.55
Other skills	2a. Basic and practical skills	4.21	4.08	0.70
	2b. Social and soft skills	4.33	3.87	2.15**
	2c. Technical skills	4.12	4.18	–0.25
	2d. System skills	4.36	4.35	0.05
	2e. Resource management skills	4.40	4.15	1.20

		Non-Robotics-adopters	Robotics-adopters	*t*-test
Digital skills		4.40	3.77	2.90***
Other skills		4.28	3.89	1.90*
Digital skills	1a. Information and data literacy	4.49	3.96	2.15**
	1b. Communication and collaboration	4.43	3.73	2.70***
	1c. Digital content creation	4.04	3.61	1.25
	1d. Safety	4.59	3.87	3.30***
	1e. Problem solving	4.43	4.08	1.65*
Other skills	2a. Basic and practical skills	4.21	3.99	1.05
	2b. Social and soft skills	4.32	3.76	2.40**
	2c. Technical skills	4.16	3.87	1.05
	2d. System skills	4.38	4.20	0.70
	2e. Resource management skills	4.41	3.96	2.05**

		Non-3D-Printing-adopters	3D-Printing-adopters	*t*-test
Digital skills		4.32	4.23	0.35
Other skills		4.25	4.08	0.65
Digital skills	1a. Information and data literacy	4.43	4.31	0.40
	1b. Communication and collaboration	4.35	4.26	0.30
	1c. Digital content creation	3.95	4.39	–1.05
	1d. Safety	4.54	4.14	1.45
	1e. Problem solving	4.42	4.05	1.40
Other skills	2a. Basic and practical skills	4.19	4.21	–0.05
	2b. Social and soft skills	4.28	4.08	0.65
	2c. Technical skills	4.16	3.79	1.05
	2d. System skills	4.36	4.33	0.10
	2e. Resource management skills	4.37	4.32	0.15

Note: ***p<0.01, ** p<0.05, *p<0.1

Table C.7 Importance of digital and non-digital skills for adopters of only "intangible" DTs and adopters of both "intangible" and "tangible" DTs

		Only-intangible-DT adopters	Both-intangible-and-tangible-DT adopters	*t*-test
Digital skills		4.43	4.27	1.05
Other skills		4.36	4.10	1.85
Digital skills	1a. Information and data literacy	4.56	4.27	1.65
	1b. Communication and collaboration	4.47	4.23	1.35
	1c. Digital content creation	4.04	4.17	–0.50
	1d. Safety	4.61	4.35	1.55
	1e. Problem solving	4.45	4.37	0.55
Other skills	2a. Basic and practical skills	4.30	4.07	1.45
	2b. Social and soft skills	4.44	4.01	2.60
	2c. Technical skills	4.18	4.06	0.60
	2d. System skills	4.41	4.37	0.25
	2e. Resource management skills	4.46	4.26	1.20

Note: ***p<0.01, ** p<0.05, *p<0.1