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Digital transformation in firms: determinants of technology adoption and implications for performance

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Abstract

Advanced digital technologies (DTs) such as AI, Big Data, Cloud Computing, 3D printing, IoT, and Robotics are known for their potential to be pervasive and generate disruptive change. Despite this, there is limited evidence regarding the factors that motivate or hinder technology adoption. This study, based on an original survey of firms in Greater Manchester, aims to shed light on the determinants of DT adoption, including underlying motivations, potential barriers, and skills deficits. Additionally, it explores the influence of digitalisation and skills on firms' performance. Our results suggest that while different DTs are at varying stages of technology diffusion, they are characterised by complementarity and are often jointly adopted. Furthermore, the adoption of DTs in SMEs and younger firms, coupled with the presence of appropriate (digital and non-digital) skills, constitutes a pivotal synergy that significantly influences firms' productivity levels.

Keywords: digital transformation; adoption; skills; motivations; barriers; productivity; firms

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Introduction

The proliferation of advanced digital technologies (DTs), such as Artificial Intelligence (AI), Big Data, Cloud Computing, 3D Printing/Additive Manufacturing, Internet of Things (IoT), and Robotics, is resulting in a significant transformation of product and process development, production, and delivery. These technologies, collectively thought of as part of Industry 4.0 (e.g., Schwab, 2017), are considered key drivers of innovation, requiring a higher demand for human labour and enhanced job quality (Lane and Saint Martin, 2021). They have become increasingly pervasive, and their adoption has had a profound impact on the economy and society, including labour markets and skills (Evangelista et al., 2014; Oduro et al., 2023). Although this process requires companies to reconsider their activities and workers' skills, including up-skilling and re-skilling to perform netasks and jobs, there are only a few studies that have examined the relationship between the adoption of DTs, skillset composition, and their effect on firms' performance—a key element of the productivity puzzle of digital technologies (Bughin et al., 2018).

There are two main reasons for this gap in the literature. First, with few exceptions (see, for example, Lane et al., 2023; Benassi et al., 2022), most studies have analysed the relationship between DTs and firm performance at an aggregate level using nationwide data or industry measures of robot diffusion (Acemoglu and Restrepo, 2020), information technology (Bessen, 2002), and patents (Autor and Salomons, 2018) as proxies for automation on the country or industry-level total factor productivity (TFP), leaving firm-level analyses largely understudied. These studies make the crucial assumption that all firms in a given industry and/or specific geographical context have the same ability and willingness to adopt digital technologies. In addition, the literature emphasising the role of labour-saving technologies on firms' outcomes (e.g., Bessen et al., 2019) has been unable to empirically link firms' performance with changes in the workers' skills structure as an important determinant of technology diffusion. Indeed, in the labour economics literature, skills and tasks are usually 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, the two concepts are fundamentally different, as tasks are about the execution of activities, whereas skills are abilities of individuals who carry out tasks, which may or may not be task-specific. Thus, a better understanding of the associations between the adoption of DTs and the associated skills is needed to ensure that companies' current and future strategic skills needs are met and to avoid stunted productivity and the negative impact on economic growth.

The second reason is the lack of firm-level data on the adoption of DTs in the literature (one exception is Leigh et al., 2022, who look at robot adoption) that allows the analysis of firm-level factors behind adoption or lack of it. Researchers have discussed the factors associated with firms' digitalisation (Björkdahl, 2020; Andersson et al., 2023) as well as the relationship between adopting DTs and firms' performance (Matarazzo et al., 2021; Ribeiro-Navarrete et al., 2021; Cirillo et al., 2023; Forgione and Migliardo, 2023), including innovation performance (Marion and Fixson, 2021; Usai et al., 2021). This is particularly important under the "modern productivity paradox," in which promising technologies initially fail—sometimes for decades—to deliver on the promise of improving productivity (Brynjolfsson et al., 2019). Nevertheless, direct evidence remains largely absent as to how companies are behaving in the digital transformation or industry revolution (Cefis et al., 2023). Lack of firm-level data has been cited as a critical impediment to understanding how DTs impact workers and firms (Seamans and Raj, 2018).

This paper analyses the determinants of DT adoption by looking at motivations and barriers behind the adoption of emerging advanced DTs. It also studies the dynamics related to skills needs to solve the puzzle of the effect of technology adoption on firm performance. It answers the following research questions: how pervasive is the adoption and use of advanced DTs? What are the factors, including skills, that affect the adoption of advanced technologies by firms? Does the adoption of DTs contribute to firm's improved performance? It contributes to the economics and management of innovation literature in three ways: (1) it reveals patterns of firms' adoption of DTs; (2) it identifies determinants of DTs adoption, including the underlying motivations and potential barriers and skills deficit, towards digital transformation within firms; and (3) it explores the influence of digitalisation and skills on firms' performance by assessing the "productivity paradox" of DTs. To address these research questions, this paper uses a unique survey on the adoption of advanced DTs in Greater Manchester. Greater Manchester offers a distinctive case study. Being the first industrial city after the first industrial revolution, it stands out as a region that has witnessed a significant drive, both from public and private sectors, towards digital transformations, with the aim of positioning itself as a leading digital city-region at both national and international levels (GMCA, 2020, 2023; Tech Nation, 2020; The Data City, 2020; CBRE, 2022).

The paper begins with a review of the literature on the main technologies in Industry 4.0 and their relationship with different firms' characteristics, including skills, followed by the presentation of the empirical context and data gathered. In the methodology section, we present the empirical strategy which combines a descriptive approach with a machine learning prediction method, random forest. Next, the results section first discusses the pervasiveness of DTs adoption and, second, the impact of adopting DTs on firms' performance. The paper finalises with some conclusions and implications for managerial practice and policymaking.

Literature review

Digital technologies within Industry 4.0

'Industry 4.0' (Schwab, 2017), also labelled the fourth industrial revolution (4IR), refers to a series of multi-layered, intertwined, and possibly convergent technologies that have emerged in the last few decades (Gilchrist, 2016), where businesses could benefit in terms of increased flexibility (Baldwin and Clark, 2000), improved automation (Brynjolfsson and McAfee, 2014), reduced costs (ibid.), and increased productivity or other performance measures, such as reduced time to market (Graetz and Michaels, 2018).

Digital technologies (DTs) are considered enabling technologies with the potential for significant change in adopting firms and markets, although they present different degrees of pervasiveness, high dynamism, and complementarities (Martinelli et al., 2021; Brynjolfsson and Milgrom, 2013). Meanwhile, there is a growing consensus that, despite the great potential of these technologies, little evidence has been detected as to their actual impact on aggregate productivity statistics (Brynjolfsson et al., 2021), in part due to the lack of firm-level data on the adoption of DTs, a critical impediment to understanding how DTs impact on workers and firms (Seamans and Raj, 2018). The absence of direct evidence on how companies are behaving in the digital transformation or industry revolution (Cefis et al., 2023) 'hinders evidence-based decision-making at all levels of government and society' (Zolas et al., 2020). Nevertheless, the dynamism of these advanced technologies, in terms of the rate of development, as measured by patent applications, has been demonstrated in the literature (Benassi et al., 2020; EPO, 2020; Martinelli et al., 2021).

Ascribable to their broad and varied applications, the literature has recorded multiple technologies within the 4IR. This study discusses and analyses the adoption of six specific advanced technologies: Artificial Intelligence (AI); Big Data, Cloud Computing, 3D printing/Additive Manufacturing, Internet of Things (IoT), and Robotics. They are shortly defined in Table 1.

Insert Table 1 around here

Skills as a neglected factor in the adoption of DTs

Historically, several factors that influence the adoption of DTs, such as those related to firm characteristics, have been identified and well-documented in the literature (e.g., Cho et al., 2023). For example, large firms exhibit a higher propensity to adopt digital technologies due to accumulated knowledge and technology capital (Gibbs and Kraemer, 2004), as well as more financial resources or the opportunity to access them. This result has been corroborated recently by Zolas et al. (2020) for the US case. They find that the adoption of advanced technology is rare and generally skewed towards larger and older firms (see also Cho et al., 2023 for a similar result). However, this result could differ by the type of technology because younger firms are more likely to adopt certain types of hardware compared to older firms (DeStefano et al., 2017). For example, AI is currently more likely to be adopted by larger and more capital-intensive firms (which tend to be more productive), but productivity gains are small after accounting for observable differences between firms (OECD, 2023). Instead, it has been recognised that Cloud Computing is particularly beneficial to smaller firms because it has less to do with size, productivity, or asset use (Cho et al., 2023).

The adoption of DTs often also requires firms' readiness and/or business transformation (Gfrerer et al., 2021), including workforce development, adequate skillset, as well as a new set of varied skills such as those related to creativity, flexibility, critical thinking, or problem-solving. This is because higher and all-rounded skilled workers tend to adopt and adapt to new technologies faster and more efficiently (Nedelkoska and Quintini, 2018). Indeed, some authors argue that technology and skills are complementary (Saunders and Brynjolfsson, 2016; Brynjolfsson et al., 2017). According to Nicoletti et al. (2020), there exists a complementarity between advanced technologies and skills, evidenced by the fact that DT adoption is more widespread in environments that are characterised by greater availability of ICT skills – especially ICT literacy and training of low-skilled workers. In a recent report comparing different OECD countries, Manca (2023) recognised that while AI skills are becoming highly important, other high-level cognitive skills, including creative problem-solving, and transversal skills such as social skills (e.g., communication, teamwork, collaboration, negotiation, presentation) and management skills (e.g., project management, staff supervision and management, mentoring, leadership), are still complementary. However, skills and tasks are usually treated interchangeably in the literature, assuming that skills are defined as a vector of different abilities needed to perform specific tasks (Autor et al., 2003) and that, therefore, there is a direct correspondence between the two. However, individuals' skillsets could change and, by adopting new technologies, workers should be prepared to and may (or may be required to) adjust their skillsets to perform new or redefined tasks.

In sum, skill requirements are evolving within and across organisations and industries, resulting in redundancies or the elimination of existing skills as well as the need for new (digital) skills (Autor et al., 2015; Zysman and Kenney, 2018). Thus, a better understanding of the dynamics underlying the adoption of DTs and associated skills in addition to other firm's characteristics is needed to ensure that companies' current and future strategic skill needs are satisfied and to avoid stunted productivity and a negative impact on economic growth.

The impact of adopting digital technologies on firms' performance

The diffusion of DTs and its impact on transforming labour market outputs of businesses and economies has been well-documented in the literature, often in relation to automation (see, for example, Autor et al., 2003; Van Roy et al., 2018; Acemoglu and Restrepo 2020; Klenert et al., 2020). Phenomena like job polarisation based on the 'task-based approach' (Autor et al., 2003) are considered one of the major factors behind the structural transformation of occupations and labour markets (Autor and Dorn, 2013; Goos and Manning, 2007) as well as business models (Loebbecke and Picot, 2015).

More recently, studies have discussed the relationships between DTs at the firm level and productivity (Cathles et al., 2020; Martínez-Caro et al., 2020), innovation (Usai et al., 2021; Blichfeldt and Faullant, 2021), internationalisation (Cassetta et al., 2020), or financial and non-financial performance (Baabdullah et al., 2021; Rialti et al., 2019). Notably, Oduro and colleagues (2023) conducted a meta-analysis of 109 relevant scholarly articles and found that four DTs (i.e., AI, Big Data Analytics, Internet of Things/cyber-physical systems, and 3D Printing) have a positive influence on firm performance.

Other studies have looked at one specific component of firm performance: productivity. For example, Graetz and Michaels (2018) observe that the adoption of robots raises labour productivity and total factor productivity in industries. Similarly, Ballestar et al. (2020) link the use of robots to labour productivity in small and medium-sized manufacturing enterprises in Spain, finding associations between the use of robotic devices and higher productivity on the one hand and higher employment rates on the other hand. More conservative voices question the potential of DTs in the current digital era. In particular, they argue that the adoption of new technologies is understood to bring productivity gains but, historically, a 'productivity paradox' has been observed: the adoption of information and communication technology (ICT) in the 1990s did not result in any significant productivity gain (Brynjolfsson, 1993). Analysing the case of AI, Brynjolfsson et al. (2021) conclude that although this technology holds great potential, there is little evidence of aggregate productivity gains yet (the 'modern productivity paradox'). This is because while the adoption of new technologies is expected to generate productivity gains, they may also be associated with higher labour costs (for needing workers with new, more in-demand skills), training and learning, and significant capital investment (Zolas et al., 2020). Among the few studies analysing DTs and productivity at the firm level, OECD (2023) suggests a modest impact on productivity, while Benassi et al. (2022) conclude that firm productivity is positively and significantly related to the development of 4IR technologies, specifically guided by the domains of wireless technology and of AI, cognitive computing, and Big Data analytics, whereas firm profitability does not appear to be affected. However, both present some limitations in the approach to measure technology adoption: the former looks at wages while the latter uses patents as a proxy for technology adoption when they are indicators of technological invention. In addition, there is little consideration in these studies on the role of skills. This is one aspect that we intend to unveil with our study.

Empirical strategy

The context

The empirical setting of this paper is the Greater Manchester area in the UK. Driven by the rise of textile manufacturing during the industrial revolution in the 19th century, Manchester and its surrounding area, called Greater Manchester, achieved its 'unplanned' transformation from a Lancastrian manorial township into the world's first industrial city. Today, Greater Manchester has a £5 billion digital ecosystem, which consists of more than 10,000 businesses with a total number of more than 86,000 employees in sectors such as AI, cybersecurity, e-commerce, and gaming (GMCA, 2020). With the digital, creative, and tech sectors as the fastest-growing sector in its city-region (GMCA, 2020; 2023), Manchester is becoming the top digital technology city in the UK outside of London (The Data City, 2020; CBRE, 2022), 'a national leader in IoT industries' (Tech Nation, 2020), and 'Europe's fastest-growing major tech cluster' in terms of investment (ibid.). In the last few years, there has been a policy push to that end. The Greater Manchester Combined Authority (GMCA) launched in 2019 the Greater Manchester Local Industrial Strategy, which includes 'Digital' as one of the four priorities (GMCA, 2019); and in 2020 the 'Greater Manchester Digital Blueprint' set out a three-year ambitious plan with aspirations for the city-region to self-propel its way into the top five digital cities across Europe (GMCA, 2020). Following the challenging times due to the COVID-19 pandemic, and with an expected investment of £16.5M in digital infrastructures, the adoption of DTs continues to grow, although at a relatively slower pace than expected. In this regard, the Local Industrial Strategy of the Greater Manchester region seizes opportunities in the potential of the digital transformation to create better quality, future-facing jobs in all sectors of the economy (GMCA, 2019). Digital technologies and digital skills are key elements of this transformation, and this study helps identify the characteristics of firms leading the race of technology adoption, the most relevant skills associated with DTs, and the impact of technology adoption.

Data collection

The data for the empirical analysis has been collected through a bespoke authors-administered survey on the Adoption of Digital Technologies and Skills (ADiTS)[1], which represents a pioneering effort to understand the extent of the adoption of six advanced DTs - AI, Big Data, Cloud Computing, 3D printing, IoT, and Robotics - among businesses in Greater Manchester. The questionnaire was built on the technology adoption section of the US 2019 Annual Business Survey (ABS)[2] and various studies on skills, including the European Digital Competence Framework for Citizens (DigComp), the US Occupational Information Network (O*NET) system, and the UK Employer Skills Survey (ESS). After a pre-test with six GMCC affiliated companies that resulted in some adjustment in the wording and categories of the survey, the data was collected between April and July 2022. During this time, 2,800 local firm members of the Greater Manchester Chamber of Commerce received the questionnaire, of which 120 participated, with a response rate of 4.3%[3]. The survey is structured in three parts, including 1) key concepts and measures related to the adoption of DTs, motivations for and barriers to adopt DTs; 2) impact of DT adoption on productivity, and 3) the importance of digital and non-digital skills. The questions relevant to the present paper are included in the annex.

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1 The ONS UK E-Commerce Survey covers some but not all of the technologies used here, namely, cloud computing, big data, 3D printing and robotics. It does not include specific questions related to motivations and barriers for technology adoption nor the effect on productivity.

[2] The technology adoption section was run in the 2019 ABS questionnaire. More information available here: https://www.census.gov/programs-surveys/abs/technical-documentation/surveys-instructions.2019.html#list-tab-1830657189 .

[3] The response rate appears on the low side. This might be due to the survey being sent to a large number of non-active affiliated members of GMCC who are not highly engaged with their activities and therefore are less responsive to these initiatives.

Variables

This section presents the variables from the survey to measure adoption, motivations and barriers, impact of DTs, as well as skills.

Adoption of DTs: Firms were asked about their level of adoption of the six DTs, measured on a 5-point Likert scale based on the following options: ‘did not use’, ‘tested, but not used’, ‘low use’, ‘moderate use’, and ‘high use’.

Motivations and barriers to adopt DTs: For the adoption of each DT, the survey asked firms about six motivations to adopt a specific DT, 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’. Similarly, respondents were asked about the barriers to adopting each individual DT, 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 DTs on productivity: Our survey considered seven elements related to the consequences of DT 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 DT on each of these aspects was measured using a 5-point Likert scale: ‘decreased considerably’, ‘decreased’, ‘did not change’, ‘increased’, and ‘increased considerably’. Then we compute the percentage of companies reporting an increase (combining those answering ‘increased’ and ‘increased considerably’) or decrease (combining ‘decreased considerably’ and ‘decreased’) respectively for each element.

Importance of skills: The questionnaire captured the relative importance of skills categorised into two groups: digital skills and other non-digital skills. Table 2 lists the key five digital and five non-digital skills included in this paper. Each of the ten categories of skills has multiple elements, and the current value is calculated as the average of the subcomponents (for more details, see Massini et al., 2022). Skills variables are measured on a 5-point Likert scale: ‘not at all important’, ‘somewhat important’, ‘neither important nor unimportant’, ‘somewhat important’, and ‘very important’.

Insert Table 2 about here

Firms’ Characteristics: Three variables related to the characteristics of the firms were also included in the questionnaire. First, the type of organisation distinguishing between private or public organisations; sector differentiating between manufacturing (high and medium tech versus low tech) and services (including knowledge-intensive services); age, and firm size (small and medium enterprises - SMEs - versus large firms).

Methodology

The empirical analysis comprises two parts. First, we carry out conventional descriptive analyses of the survey data to provide a snapshot of the extent to which firms in the Greater Manchester city region adopt DTs. This helps to address our questions on technology pervasiveness and dynamics of DT adoption and skills.

The second part, and in order to address the third question, utilises prediction techniques on the adoption of DTs and their impact on firms' performance characterised through self-reported assessment of productivity gains. Our data is a wide sample with a large number of variables but a relatively small number of observations, which makes it difficult to use traditional statistical models for statistical inference. Therefore, in order to identify predictively the most significant drivers of technology adoption and productivity impact, we use a tree-based machine learning technique known as Random Forest (RF) (Breiman, 2001; James et al., 2013; Hut and Oster 2022). In addition, we explore interactions (complementarities) between DTs and firm characteristics and assets in driving firm performance, which have been emphasised in the recent theoretical literature (Brynjolfsson and Milgrom, 2012).

We adopt the permutation-based approach, also known as the 'Breiman-Cutler importance' (Breiman, 2001), for estimating the predictive importance of the variables used in each model. This technique estimates the decrease in the prediction accuracy of the RF model resulting from randomly permuting the values of an individual predictor (variable) while holding the values of all other predictors fixed. The algorithm then ranks the predictors based on the degree to which permuting their values reduces the prediction accuracy[4]. The Variable Importance (VIMP) ranking is sometimes used as a criterion to select variables. That is, the researcher heuristically examines the VIMP ranking to identify a point where there is a noticeable drop in the VIMP of the variables and selects the variables above the point as those predictively most significant (Ishwaran et al., 2011; Makariou et al., 2021). We start with a rich model that includes intuitively important predictors of adoption and productivity without significant missing values. We first train an RF model on this rich

[4] Prediction accuracy is captured by criteria such as mean-squared prediction error for continuous variables and mean decrease in accuracy for discrete variables (Ishwaran et al., 2011; Makariou et al., 2021).

model to exclude variables with a mean decrease in accuracy close to zero (that is, non-relevant variables). We next retrain the model on the remaining predictors to rank the variables. Training an RF model requires setting several hyperparameters, such as the size of the forest, the depth of the trees, and the minimum number of observations in each bucket. We select the hyperparameters using cross-validation.

In addition to identifying drivers of DT adoption, we are also interested in understanding complementarities among (or configurations of) firm characteristics such as size, age, (tangible and intangible -including skills-) assets and sector and DTs that drive technology adoption and firm performance. To derive these interactions, we use the R package inTrees (Deng, 2019), which implements an approach proposed by Friedman and Popescu (2008). The technique trains an RF consisting of trees with a depth of two or three layers of variables and searches for the most predictively significant interactions. The interactions are presented as a set of rules that show how the independent variables interact with each other to predict the response variable (adoption or productivity). We represent each rule (interaction) using an indicator variable that takes the value one when a firm satisfies the rule and zero otherwise. We test the significance of the interaction using logistic regression models.

Describing DT adoption in Greater Manchester

Our sample is based on companies (88%) in the private sector, the majority of them are from the service sector (82%), more specifically knowledge-intensive services (KIS) (66%). They are mainly Small and Medium Enterprises (SMEs), representing more than 70% of the respondents (Table 3).

Insert Table 3 about here

Figure 1 presents the rates of technology adoption among respondents. Our data show a 78% adoption rate, meaning that nearly four out of five firms have adopted at least one type of advanced DT. This result is mainly led by firms in the high-tech manufacturing and KIS sectors, reflecting the specific industrial context of the Greater Manchester city-region, made up predominantly of SMEs, where financial and other professional services have acted as the engine of jobs growth for over a decade (BEIS, 2019). Historically, professional services, some of which are indeed KIS, have been considered a 'vanguard sector' in the adoption of ICT (Barras, 1990), and since the 1970s ICTs have been considered a key element of the service-based technological revolution (Brynjolfsson and McAfee, 2014). Differently from the results in the US study, which finds that the largest and oldest firms tend to adopt more DTs (Zolas et al., 2020), interestingly our survey documents the adoption of DTs among SMEs.

Moving on to the adoption of specific technologies, Cloud Computing is the most widespread technology, adopted by 70% of the sampled firms. This result is in line with the data relative to US firms, where Cloud Computing is adopted by different business functions within firms (Zolas et al., 2020). The high adoption rate for this technology can be due to the inclusion in this category of widespread internet tools and e-commerce, which are applicable to smaller firms (Cho et al., 2023) and can substitute costly in-house computing capabilities with outsourced IT services for less-resourced small firms (Jin and McElheran, 2017). However, the adoption of the other five advanced DTs appears to be relatively low overall (only one out of four firms adopts any of them), suggesting that they are at an earlier stage of diffusion. 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 indicate the importance of bundling data and intangibles (Haskel and Westlake,

2017) for adopters of DTs (mostly service companies in our sample), rather than a dependence on technologies related to the digitalisation of industrial sectors (which is more the case for manufacturing firms).

Insert Figure 1 about here

Our study corroborates that the adoption of DTs often does not occur in isolation (Ciarli et al., 2021; Cho et al., 2023) and that adopters tend to introduce multiple DTs, which can complement each other. We found that 43% of the firms that adopted DTs reported adopting two or more of them. In particular, 25% of respondents reported adopting two technologies simultaneously, which is in line with European trends (Kazakova et al., 2020). The most frequent combinations of technologies jointly adopted are Cloud Computing and AI, and Cloud Computing and Big Data, supporting the importance of data and other intangibles in DT adoption. For example, firms wanting to use AI require large datasets to train their algorithms, which can be generated and collected at large scale using Big Data practices and processed and stored on Cloud Computing services (De Stefano et al., 2020; OECD, 2019).

Moving on to the motives to adopt DTs, process or method quality improvement was the most common reason to adopt DTs, which was selected by two-thirds of the adopters of any of the six technologies (see Figure 2). Product innovation, including the diversification of the portfolio of products and services, was the second most common motivation selected by half of the respondents, closely followed by processes or method upgrade. Task automation, which in the literature is often associated with the adoption of DTs (mainly industrial robots), was selected by 45% of the adopters. 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).

Insert Figure 2 about here

When asked about barriers to adopting DTs, more than half (58%) of the respondents reported that at least one DT is not applicable to them. Considering that the majority of respondents are service companies, it is likely that DTs normally used in manufacturing firms, i.e., Robotics, 3D Printing, and IoT, are not applicable to them. Amongst the barriers listed, the lack of access to the required human capital and skills is one of the main barriers reported to adopting DTs, as is its cost: 31% of the firms reported these two barriers hampering technology adoption, 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 right skills and the cost of adoption are the main internal obstacles to adopting AI (Kazakova et al., 2020).

Insert Figure 3 about here

Regarding the skills considered in the study, Figure 4 shows the average importance of both digital and non-digital skills for adopters of DTs and non-adopters. Interestingly, adopters of DTs, on average, rate the importance of all 10 skills higher than non-adopters, although most differences are not statistically significant. Only ‘problem solving’ and ‘basic and practical skills’ are statistically more important to adopters than non-adopters (Figure 4).

Insert Figure 4 about here

What drives digital technology adoption?

We expand our descriptive results using prediction techniques and explore firm factors that drive the adoption of DTs captured in our survey. Specifically, we estimate a series of RF models leading to the most optimal one in the following form:

> **Model 1**: *DT Adoption ~ Organisation Type + Turnover + Age + Size + High Tech Manuf Sector + Manuf Sector + KIS + (Average) Digital Skills + Barrier_HC + Barrier_Capital*

where DT refers to AI, Big Data, Cloud Computing, 3D printing, IoT, and Robotics. Organisation type is a dummy variable that equals 1 if the respondent is a private firm and 0 otherwise. Turnover is a dummy variable that equals 1 for firms with capital greater than the median £500K (median), and 0 otherwise. Age refers to the number of years (in logarithm) between the establishment year and the year 2023. Size is a dummy variable with the value 1 indicating large firms (50 or more employees) and 0 are SMEs (less than 50 employees). High-Tech Manufacturing, Manufacturing sector, and Knowledge Intensive Sector (KIS) are dummy variables with the value 1 if a firm is part of that sector and 0 otherwise. Barrier Human Capital (HC) and Barrier Capital are two dummy variables with the value 1 if a firm identifies that as a key barrier for technology adoption and 0 otherwise. Finally, Digital skills (average) are measured as the average scores each firm gave to skills 1a-1e in Table 2. We train an RF model for each technology category and plot the predictive importance ranking in Figure 5.

The RF model for AI adoption suggests firm size, average digital skills, financial resources (capital constraints), age, and manufacturing sector are predictively the most relevant variables. Firm size and average digital skills appear high at the top of the ranking, suggesting that permutating their values will reduce the model's predictive accuracy by 12 and 6 percent, respectively. The RF model also points to several predictively significant interactions among the explanatory variables (Table 4). We select the variables whose variable importance measure exceeds zero, that is, variables whose permutation reduces the model prediction accuracy (Ishwaran, et al., 2011). Using the predictively significant variables, we retrain the random forest model to identify potential interactions among the variables. The interactions in the AI panel suggest that older (above the first quartile of age) SMEs are less likely to adopt AI technologies while, on the contrary, younger firms are more likely to adopt AI technologies when they do not face capital constraints, reinforcing the argument that smaller companies will benefit from lower capital-intensive technologies (OECD, 2023).

Turning to the variable importance results for Big Data technologies, the RF model identifies lack of access to human capital, KIS, turnover, capital constraints, and average digital skills as predictivity relevant, but mostly are weakly significant. Among firms that adopted Big Data, 75% of firms cited lack of access to human capital as a barrier while among the firms that did not adopt Big Data, only 21% cited the barrier. Interestingly, the model also predicts that KIS are more likely to adopt Big Data. Firms with above the median turnover in our sample are twice as likely to invest in this technology. And among the firms that adopted Big Data, the likelihood of expressing financial constraints as a barrier for adoption was slightly higher (0.2) than for firms that did not adopt (0.17). The RF model uncovers several interactions between access to human capital, financial capital, and firm turnover, reported in Table 4 (Big Data panel). Firms that report having difficulty in accessing human capital but do not face capital constraints are more likely to adopt Big Data. This reinforces the importance of data collection even in the absence of the right skills and talents to hire. Similarly, firms that report having challenges in accessing human capital and their turnover fall below the sample median are more likely to adopt Big Data. Both complementarities are significant at 10%. This could be because adopting Big Data, which includes buy-in services related to this technology, might be a response to internal shortage of adequate IT internal capabilities, when firms are, however, endowed with financial capital which alleviates the human resources constraint.

The RF model for Cloud Computing reported in Figure 5 shows that turnover, firm size, age, and KIS are predictively relevant. However, they only marginally predict Cloud Computing adoption. This is likely because all firms in the sample had adopted some level of Cloud Computing, leaving no variations in the data. Table 4 shows only one significant interaction for Cloud Computing. Younger firms considering digital skills at least somewhat important (average digital skills above 1.99) are more likely to adopt this technology.

Similarly, the RF model for 3D printing reveals that our measures of firm and industry characteristics are largely predictively insignificant. Of all the explanatory variables, only age and firm size, turnover, and the dummy variables for manufacturing sector and private companies appear as slightly significant. Permutating the age values reduces the model’s accuracy by less than 4 percent in all cases. As a result, the interactions appearing in the RF model are not statistically significant (Table 4). In contrast to Cloud Computing, the lack of variety among respondents here is due to only a few firms adopting 3D printers for additive manufacturing, which clearly associates with the manufacturing sector rather than the service sector that characterises our respondents. Related to age, 3D printing could enable reshoring of manufacturing activities, i.e., repatriation of production activities previously offshored, contributing to in-house prototyping and disintermediation (Fratocchi, 2017; Bordeleau and Felden, 2019; Cefis et al., 2023), and incumbent firms could have an advantage compared to new entrants in the market due to their availability of higher resources to invest in the acquisition of the technology. This is an interesting finding because it has been argued that 3D printing provides benefits in terms of producing on a small scale and therefore allows new entrepreneurial firms to contest markets occupied by older and larger incumbent firms who have built and maintain their competitiveness on economies of scale.

The RF model predicting adopting IoT identifies several firm characteristics as predictively significant. Lack of access to human capital is the most predictively significant variable followed by digital skills, age, and organisation type. The interactions in Table 4 suggest that firms that reported difficulty in accessing human capital and considering digital skills as highly relevant (above the median 4.69) and were relatively younger (age below 3.85) were more likely to have adopted the IoT. Both interactions are statistically significant at 1% and 10%, respectively.

Finally, looking at the adoption of Robotics, the RF model suggests variables relating to turnover, firm size, age, and digital skills as predictively most significant. These results are consistent with the findings in the literature on automation that show that larger firms are more likely to invest in automation, and larger firms tend to be older (Suedekum et al., 2020). Table 4 (Robotics Panel) shows several potential complementarities, but they are not statistically significant. This is likely because in our small sample only 10% of the firms (11 companies) reported having adopted Robotics technology. Interestingly, the level of robot diffusion is at an early stage in Greater Manchester compared to other countries like the US starting to penetrate SME establishments beyond the manufacturing sector as well (Leigh et al., 2022). Nonetheless, the predicted complementarities are consistent with the findings in the literature that larger firms with higher levels of digital skills are more likely to invest in automation (Cho et al., 2023).

Insert Figure 5 about here

Insert Table 4 about here

Impact of technology adoption on firm's productivity in Greater Manchester

The impact of innovation on productivity growth in Greater Manchester is analysed in terms of technological changes that either reduce costs, increase the volume of outputs, or achieve both outcomes (Ugur and Vivarelli, 2021). As shown in Table 5, the observed impact on productivity in the region appears to stem primarily from an increase in the volume of outputs (23% through the volume of production, 39% through the number of customers, 32% through product diversification, and 30% through the type of customers), rather than cost reduction (17%) and price reduction (3%).

More specifically, Robotics and 3D Printing technologies seem to influence the volume and diversification of products in a manner analogous to traditional scaling-up or economies of scale in the manufacturing industry. On the other hand, Cloud Computing, Big Data, and AI have the potential to enable businesses to scale up by expanding their customer base. However, especially in the initial phases following the adoption of new technologies, there may be significant increases in production costs or the cost of processes. This, in turn, might necessitate an adjustment in the selling price of goods and/or services, particularly for technologies like Cloud Computing and 3D Printing.

Insert Table 5 about here

Does adoption of DTs and skills predict higher productivity?

Expanding on the previous descriptive analysis, we now present the results of the prediction techniques to learn about the effect of DTs on firm productivity. Specifically, we estimate the following model:

Model 2: *Firm productivity ~ Organisation Type + Turnover + Age + Size + High Tech Manuf Sector + Manuf Sector + KIS + (Average) Digital Skills + Barrier_HC + Barrier_Capital + AI adoption + Big Data adoption + Cloud Computing adoption + 3D Printing adoption + IoT adoption + Robotics adoption*

where productivity is measured by two alternative variables constructed from the survey: volume of outputs and production costs. The predictors are the same as in Model 1 and include also dummy variables for technology adoption in each particular technology. The results are presented in Figure 6.

The rankings suggest a relatively stronger association between the predictors and volume of production compared to cost-effect. This is in line with the results presented in the previous section where we highlighted that the impact on productivity seems to occur through an increase in the volume of outputs rather than a reduction in production costs. Permuting the values of the adoption of Cloud Computing variable or turnover in the RF model for predicting productivity measured using volume reduces the model's mean prediction accuracy by about 7 percent. And permuting the values of the Robotics adoption reduces the model's mean prediction accuracy by about 4 percent. However, as shown on the right-hand side of Figure 6, the predictors do not equally predict changes in production costs, as evidenced also by the relatively lower values of the scale at the bottom of the graph. Most variables are either negligibly predictively significant or are insignificant, and permuting the values of Cloud Computing, which is ranked in the second position, reduces the model's accuracy by less than 4 percent. Nonetheless, these results offer some evidence of the effect of DTs on performance. While a reason for the weakness of these results could be the modest size of our sample, a theoretically plausible explanation is that firms might currently lack complementary organisational skills and assets to fully benefit from the adoption of data technologies.

Table 6 reports the predictively most significant rules (routes) in the RF models for each productivity measure. All the complementarities relating to the volume measure are statistically significant at 5 and 10 percent. The interactions suggest that firms that adopted Cloud Computing and considered digital technologies very important (above 4.97) showed a higher volume of outputs. Additionally, younger firms considering digital technologies very important (above 4.8) also showed higher volume of outputs. Larger firms with turnover above the median whose average digital skills exceed 4.8 (very important) also showed higher outputs. In contrast, older firms (above the median age) that adopted Cloud Computing were associated with lower outputs. Taken together, these findings suggest that relatively younger firms with adequate digital skills who adopt Cloud Computing showed higher output levels, reinforcing our argument about the importance of looking together at the technology and human capital to maximize the returns from technology adoption. The second panel in Table 6 presents the predictively significant interactions for the cost-based productivity measure. However, although the combinations of factors are theoretically meaningful, the complementarities are not statistically significant.

Insert Figure 6 about here

Insert Table 6 about here

Conclusions

This study provides evidence on the adoption of six different digital technologies using firm-level data in Greater Manchester. This allows us to present novel results by examining the pervasiveness, predictors, and impact of I4.0 DTs in firms. Our study corroborates the importance of conducting more fine-grained research on the adoption of DTs at the firm level to understand drivers, barriers, and the impact on firms' performance. Specifically, there are five main takeaways from the results presented and discussed here.

First, although the adoption of DTs is slower than expected considering the widespread hype around DTs, only one out of four firms has adopted a non-Cloud Computing DT in Greater Manchester. Interestingly, we observe that different DTs are at different stages of diffusion. Cloud Computing is at a rather advanced stage and is the most widespread technology close to saturation levels. On the contrary, the adoption rate of the other five advanced DTs appears to be relatively low overall, suggesting that they are at an earlier stage of technology penetration (i.e., firms are testing or making low use of the DTs as opposed to high/medium use). Big Data and AI are the second most adopted technologies. As most companies have adopted Cloud Computing, this points to the importance of bundling data (AI and Big Data) for firms adopting DTs in Greater Manchester and highlights the importance of intangibles as a key resource for firms. This relates to our second conclusion that DTs are complementary. In our study, the adoption of one technology tends to be accompanied by the adoption of other technologies, enabling adopters to fully benefit from their joint use and higher returns on the investment in these technologies.

SMEs and younger firms are leading technology adoption (mainly AI, Cloud Computing, and IoT), especially in the knowledge-intensive sector. These firms take advantage of the lower capital-intensive nature of these advanced DTs as well as the broader versatility and applicability of these innovations (Corradini et al., 2021). It is important now to develop appropriate tools to evaluate the use of DTs as a cost-effective method to enhance their competitiveness. Older and larger firms tend to focus more on manufacture-oriented technologies such as 3D printing and Robotics, which is also supported by the empirical evidence found in the US (Zolas et al., 2020).

Third, the main reason to adopt DTs is for improving the quality or reliability of processes or methods, a non-disruptive, incremental change to production processes highlighted in Waldman-Brown (2020) as one of the reasons why SMEs consider upgrading their technology. Instead, there are multiple factors that hamper the adoption of DTs. The key barriers to adopting DTs relate to the cost of the technologies as well as the lack of human capital with the appropriate skills. Thus, skills represent a remarkably important intangible asset for firms and if they are a key factor in the adoption of digital technologies, training should be recognised as a crucial approach to narrow the gap between employers' needs and employees' capabilities.

Fourth, it has been recognised that innovation can drive productivity growth through technological change that reduces the cost, increases the volume of outputs or both (Ugur and Vivarelli, 2021). Our study, based on RF prediction techniques, suggests that the impact of DTs adoption on productivity was achieved mainly through the latter. In particular, relatively younger firms with adequate digital skills who adopted Cloud Computing showed a higher volume of outputs. We unpacked the complementarities between predictors of DTs and firm's productivity to understand how firms can optimise resources for technology adoption and impact. We found that although firms' characteristics, including size, turnover, and age, are the strongest predictors for the adoption of AI, Cloud Computing, 3D Printing, and Robotics, the adoption of technologies such as Big Data and IoT tends to depend on firms' internal capabilities and human capital. These results corroborate the importance of conducting fine-grained analyses of DTs, skills, and firms' characteristics, as technology adoption is a necessary but not sufficient condition to maximize returns from investment.

Last but not least, some interesting differences were found in terms of the skills needed for the adoption of DTs. Adopters of DTs tend to rank both digital and non-digital skills more highly than non-adopters, with key differences on the 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. It is also worth noting that digital skills requirements are technology- and sector-specific.

Managerial and policy implications

The results presented here inform managers and policymakers. At the business level, our results inform practitioners about the unexpected gains of DT adoption and help them identify and anticipate skills, both specialised in digital competencies but also complemented with transversal skills, needs that their firms might require once they embark on the adoption of particular technologies and their integration into their activities. For policymakers who are responsible for leveling up regional economic growth, our results provide insights for making informed decisions on the best strategies, incentives, and support to adopt advanced DTs, implementing on-the-job training, as well as considering developing educational programs to create an adequate supply of workers with the required combination of skills for a fruitful adoption of DTs. This study provides specific insights into initiatives like the Local Skills Improvement Plan (LSIP) in Greater Manchester as it covers key elements to understand current skills needs in relation to the adoption of digital technologies, a key element to support firms and shape the skills provision following the Skills for Jobs White Paper.

It is important to recognise some limitations of this study. First, although results have been compared with other cases of adoption of DTs in different countries, this study is based on a single region, Greater Manchester, particularly characterised by SMEs and where the financial and other professional services sectors have represented the engine of jobs growth for over a decade (BEIS, 2019). Therefore, although we add to the literature by using fine grained, firm level data, we acknowledge that the results are specific to the configuration of the industrial and economic setting in Greater Manchester. Indeed, our data could be biased towards certain service sectors represented in the membership of the GMCC.

Second, in terms of conceptualization of DTs, we have restricted the scope to a set of six technologies. However, there are other digital technologies available, e.g., blockchain, virtual reality, etc., which would be interesting to analyse, also in relation to the implications on skills and adopters' performance. Third, due to the anonymization process, we were not able to contrast self-reported information with secondary data, which could lead to response biases and over positive results about technology adoption. Finally, the sample used in the study, 120 cases, is somewhat small, in particular to understand adoption of some DTs like Robotics or 3D printers. For that reason, results should be interpreted with caution.

Data availability statement

The participants of this study did not give written consent for their data to be shared publicly, so due to the sensitive nature of the research supporting data is not available.

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Table 1. Definition of the six Digital Technologies

Digital Technology	Definition
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 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 volume 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	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.
Robots	Automatically controlled, reprogrammable, and multipurpose machines used in automated operations in industrial and service environments. For example, automation in the assembling line.

Source: Massini et al. (2022)

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

Table 3. Key demographics of respondents to the AdiTS survey

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%	

Table 4. Two-Way Complementarities for Technology adoption

Digital Technology	Rules	Complementarities	Coefficients
AI	1	Age > 1.7 & Firm Size = SMEs	-3.811 (1.923)**
	2	Age <= 1.7 & Capital Barrier= 0	2.63 (1.394)*
Big Data	1	Human capital Barrier = 1 & Capital Barrier = 0	1.99 (1.210)*
	2	Human capital Barrier = 1 & Turnover <£500K	1.621 (0.959)*
Cloud Computing	1	Age > 2.44 & KIS = 1	23 (330)
	2	Age <= 4.1 & Digital Skills > 1.99	6 (2.817)**
	3	Turnover =1 & Digital Skills <= 4.72	0.331(1.468)
3D Printing	1	Turnover = 0 & Age > 2.07	-14.87 (190)
	2	Age <= 3.04 & Firm Size = Large	-2.07 (1.98)
	3	Organisation Type = Non-private firms & Age < 2.7	37 (534)
IoT	1	Human capital Barrier = 1 & Digital skills > 4.69	5.71 (2.097)***
	2	Age <= 2.29 & Age <= 3.85	2.287 (1.353)*
Robotics	1	Firm Size =Large & Digital skills > 4.97	20.719 (2694)
	2	Turnover >£500K & Age <= 2.07	24.165 (3690)

Note: This table tests the statistical significance of predictively significant interactions found in the random forest models. For each interaction, we construct an indicator variable that takes value one if the rule holds and zero otherwise. We test the significance of the rule by adding the indicator variable to a logistic regression with the predictively most significant variable for the DT in question.

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	

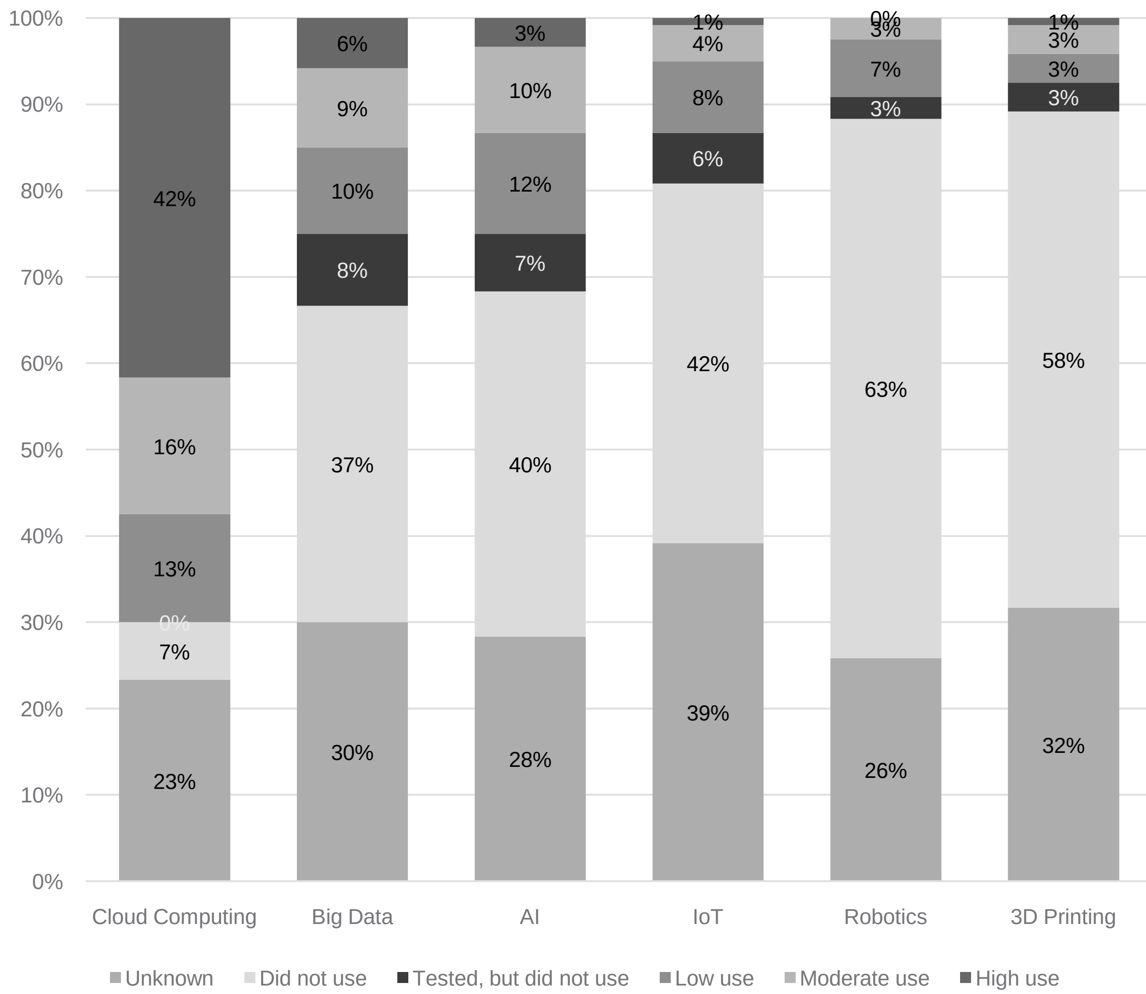
Source: Authors' own elaboration based on ADiTS survey

Table 6. Two-Way Complementarities for Firm's productivity

Productivity Measure	Rules	Complementarities	Coefficients
Volume of outputs	1	Cloud Computing Adoption = 1 & Digital Skills > 4.97	4.5 (0.043)**
	2	Age <= 3 & Digital Skills > 4.8	3.79 (1.6)**
	3	Age > 2.6 & Cloud Computing Adoption = 1	-4.79 (2.7)*
	4	Digital Skills > 4.8 & Turnover > £500K	6.19 (2.8)**
Production cost	1	Human capital barrier = 1 & Cloud Computing = 1	-0.492 (2.01)
	2	Turnover <£500K & Cloud Computing = 1	0.186 (1.172)
	3	Cloud Computing =1 & Big Data = 1	17.17 (169)

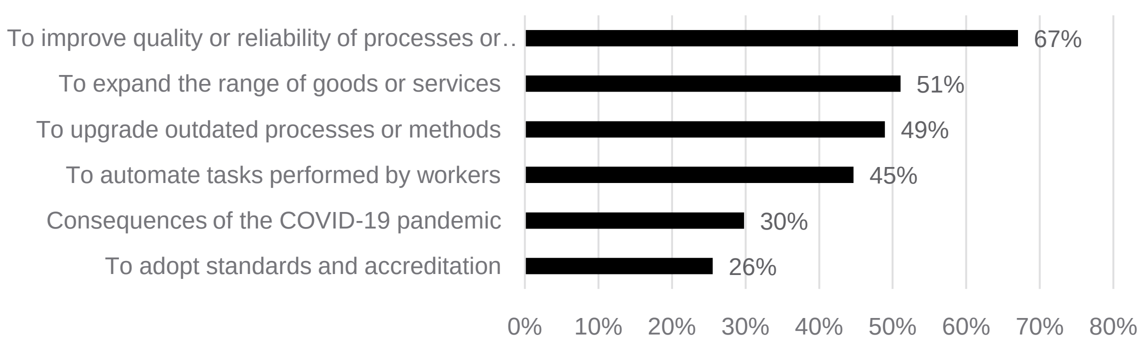
Note: This table tests complementarities among digital technologies and firm characteristics in driving productivity. We first select the predictively significant variables from the random forest for the digital technology in question and then use the variables to train a reduced random forest model with shallow trees of 2 to 3 layers. We identify potential complementarities by searching for the predictively most significant routes among the trees in the forest. We use an indicator variable that takes value one if the rule holds and otherwise zero to capture each complementarity. We test the significance of the rule by adding the indicator variable to a logistic regression that includes all the predictively significant variables for the technology in question.

Figure 1. Adoption of digital technologies (% respondents)



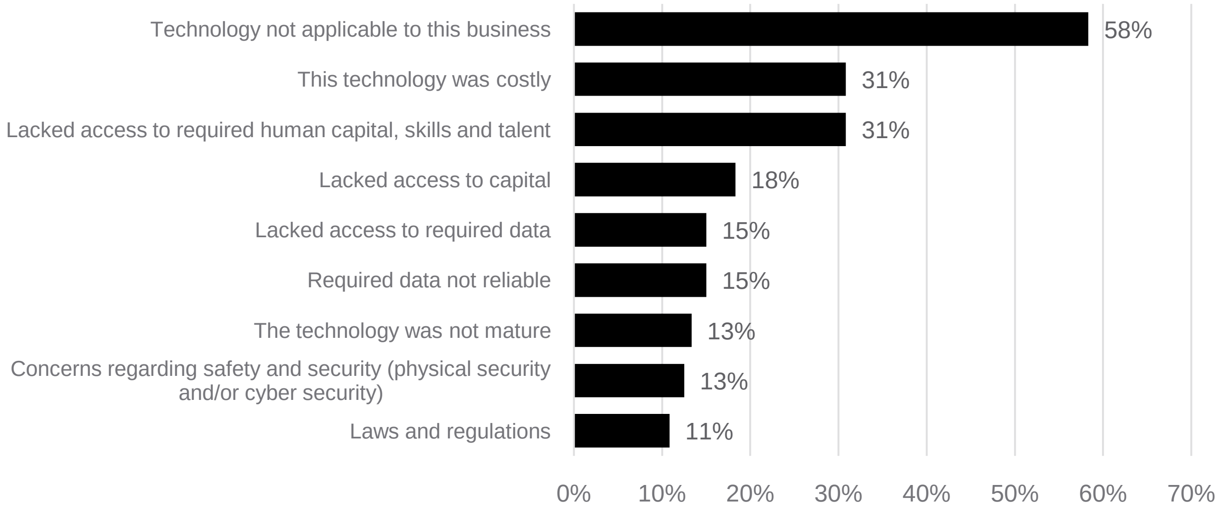
Source: Authors' own elaboration based on ADiTS survey

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



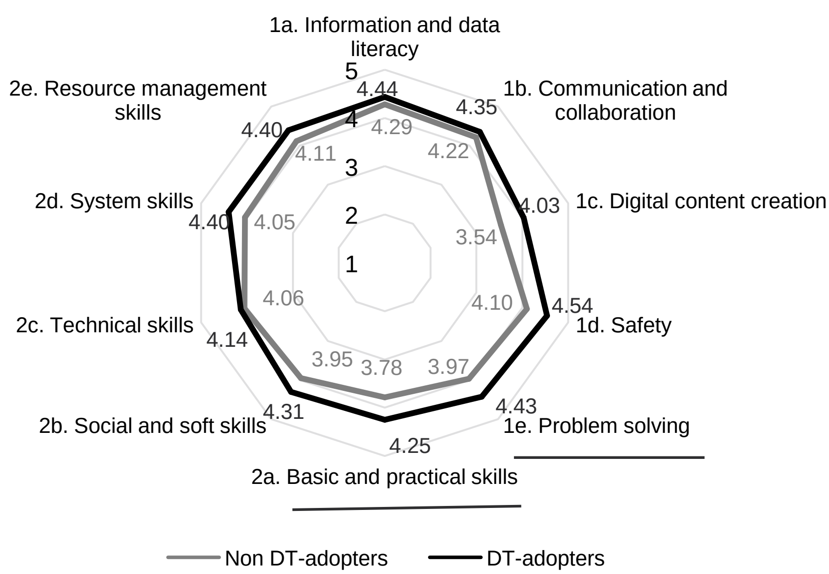
Source: Authors' own elaboration based on ADiTS survey

Figure 3. Barriers to adopt digital technologies (% respondents)



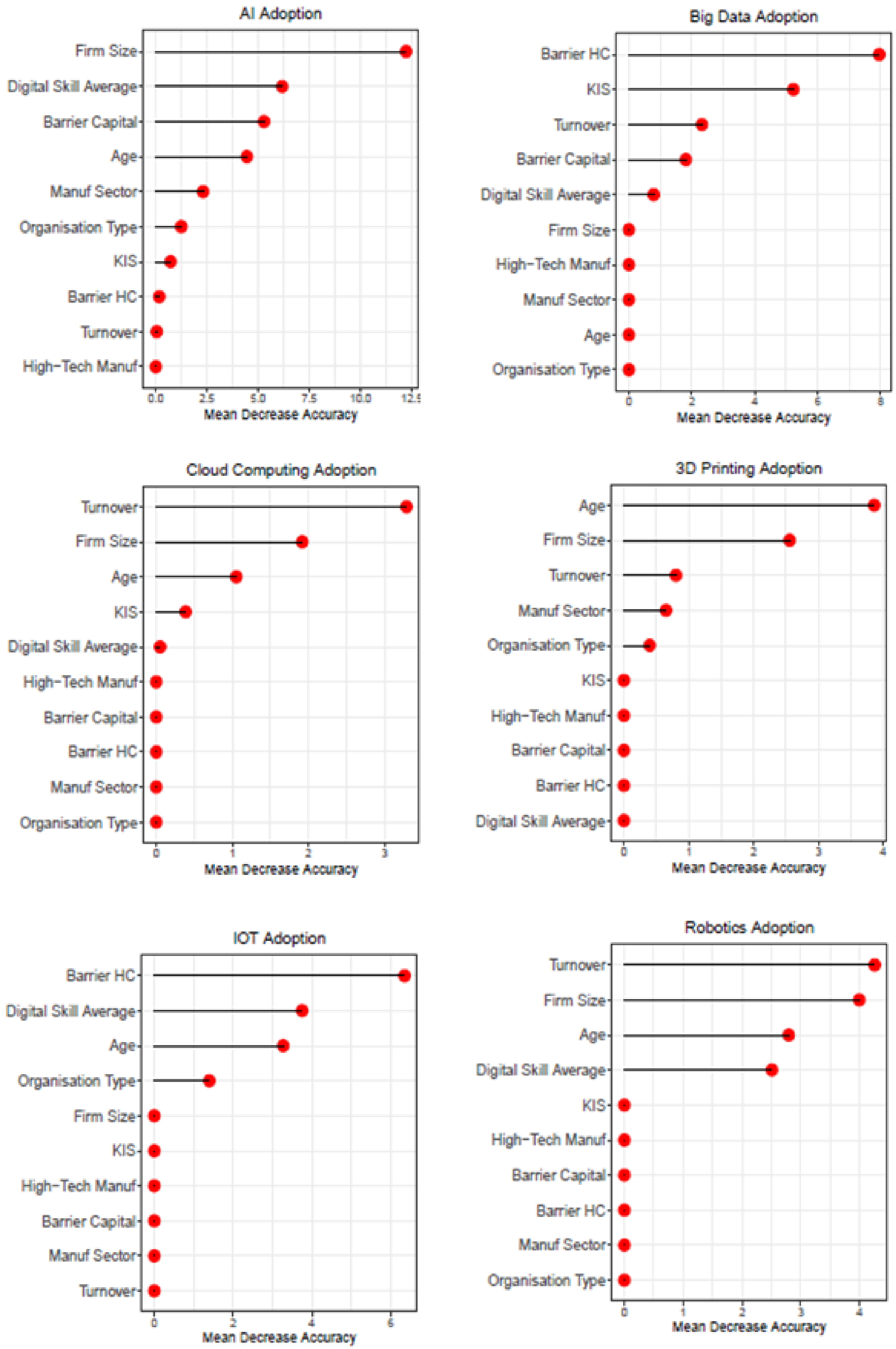
Source: Authors' own elaboration based on ADiTS survey

Figure 4. Importance of digital and non-digital skills for adopters and non-adopters of digital technologies



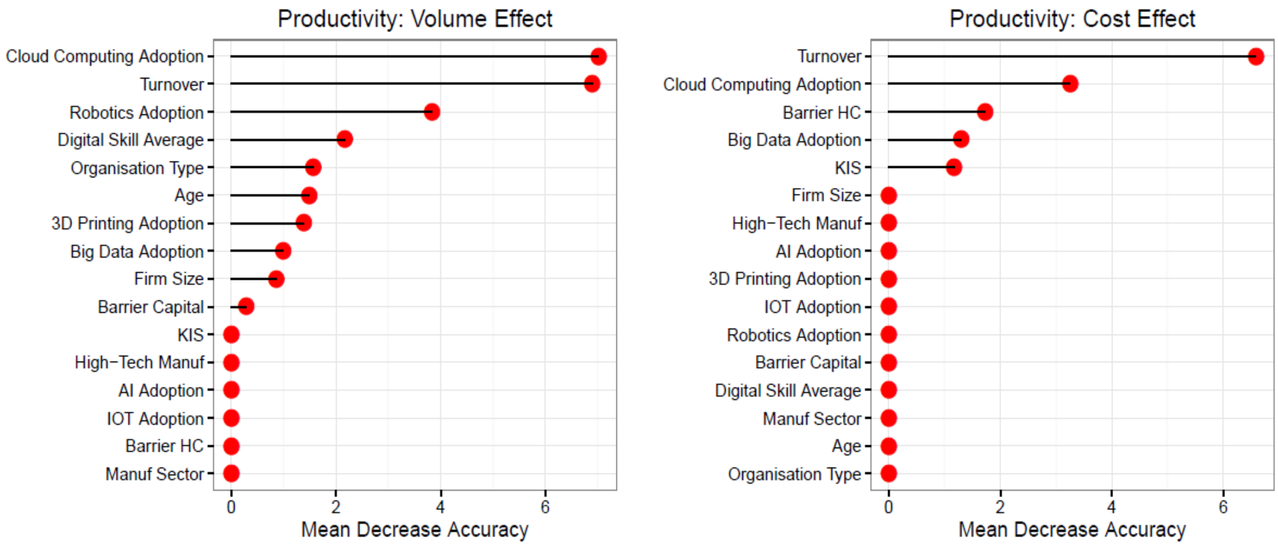
Note: Underlined results are significant variables at 5% using t-tests to compare differences withing skills for adopters. Source: Authors' own elaboration based on ADiTS survey.

Figure 5. Graphs of variables importance for digital technology adoption



Note: Value is interpreted as the percentage reduction in the predictive accuracy of each model (Variable Importance - VIMP).

Figure 6. Graphs of variables importance for firm's productivity



Note: Value is interpreted as the percentage reduction in the predictive accuracy of each model (Variable Importance - VIMP).

Annex. Relevant questions in the ADiTS questionnaire related to DTs and skills

This annex presents the key questions in the questionnaire used in this paper. For mode detailed information about the answers, please refer to Massini et al. (2022)

Digital technologies

The following questions were asked for each of the six DTs considered.

1. During the 3-year period 1 January 2019 to 31 December 2021, to what extent did this business or organisation use the [*Insert one of the DTs here*]?

2. During the 3-year period 1 January 2019 to 31 December 2021, why did this business or organisation adopt or use the [*Insert one of the DTs here*]?

3. During the 3-year period 1 January 2019 to 31 December 2021, what impact did the [*Insert one of the DTs here*] have on the following factors in relation to the productivity of this business or organisation?

4. During the 3-year period 1 January 2019 to 31 December 2021, which factors adversely affected the adoption or utilisation of the [*Insert one of the DTs here*]?

Skills

1. During the 3-year period 1 January 2019 to 31 December 2021, how important were the following digital skills to your business or organisation?

2. During the 3-year period 1 January 2019 to 31 December 2021, how important were the following other skills to your business or organisation?

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