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What's driving the diffusion of next-generation digital technologies?

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ABSTRACT

The recent development and diffusion of next-generation digital technologies (NGDTs) such as artificial intelligence, the Internet of Things, big data, 3D printing, and so on are expected to have an immense impact on businesses, innovation, and society. While we know from extant research that a firm's R&D investment, intangible assets, and productivity are factors that influence technology use more generally, to date there is little known about the factors that determine how these emerging tools are used, and by who. Using Probit and OLS modeling on a survey of 12,579 South Korean firms in 2017, we conduct one of the first comprehensive examinations highlighting various firm characteristics that drive NGDT implementation. While much of the literature assesses the use of individual technologies, our research attempts to unveil the extent to which firms implement NGDTs in bundles. Our investigation shows that more than half of the firms that use NGDTs deployed multiple technologies simultaneously. One of the insightful complementarities identified in this research exists amongst technologies that generate, facilitate and demand large sums of data, including big data, IoT, cloud computing and AI. Such technologies also appear important for innovative tools such as 3D printing and robotics.

1. Introduction

Over the last decade we have witnessed a dramatic increase in the diffusion of new types of digital technologies (OECD, 2020b).[1] The rollout of fiber-optic broadband along with complementary technologies including cloud computing, the Internet of Things (IoT), data analytics and Artificial Intelligence (AI) is expected to dramatically change how firms organize, compete and engage with their customers (Iansiti and Lakhani, 2020; Andres et al., 2020; DeStefano et al., 2020b; Agrawal et al., 2018; McElheran, 2018; Brynjolfsson and McAfee, 2014). While these technologies will likely enable the growth and success of some sectors and firms, they will also lead to the inevitable demise of others (Silva et al., 2019; Calvino et al., 2015; Davis and Haltiwanger, 2014). This is likely to present several economic and social challenges, such as changes in employment demand, wage opportunities, and potentially, social unrest (Eckert et al., 2020; Acemoglu et al., 2020; Silva et al., 2019; Frey and Osborne, 2017; Fischer, 1966).

The bundling of several new and emerging complementary digital technologies — which will be referred to in this paper as Next Generation Digital Technologies (NGDTs),[2] can be seen as ushering in the ongoing economic revolution, which some have labeled "Industry 4.0" (Kagermann et al., 2011; Schwab, 2016). For this examination, we identify and classify nine distinct technologies as NGDTs: IoT, mobile devices, big data, cloud computing, AI, blockchain, virtual/augmented reality, robotics and 3D printing (Kagermann et al., 2011; Marr, 2016; OECD, 2017b). Unlike the technological advances made in the latter half of the 20th century, when computers and other digital technologies replaced their analog predecessors, NGDTs are typified by the interconnectedness of these digital technologies and flexible computing services. These technologies enable data production and the promotion of more effective data usage, facilitating automation and more accurate decision-making by firms (Schwab, 2016; Marr, 2016; Park, 2018). We specifically designate these technologies as NGDTs to avoid the pitfalls of a generic Industry 4.0 categorization, which can be used to refer to an undefined number of technologies (many of which lack an agreed-upon definition)[3] and is often connotated with the manufacturing industry specifically.

Earlier works on the types of NGDTs we analyze in this paper were typically performed in the context of Industry 4.0, these studies include theoretical discussions on the likely trajectory of technology diffusion in

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[1] Throughout this paper, we use the terms "technology" and "tools" interchangeably.

[2] This set of technologies is also referred to as Industry 4.0 in the literature (Kerin and Pham, 2019; BCG, 2021; OECD, 2017b). However much of the research has been done in the context of manufacturing firms. Yet these technologies are also diffusing among both manufacturing and service firms (OECD, 2020b).

[3] There remains no broad consensus as to what specific technologies Industry 4.0 refers to (Culot et al., 2020). This prompted us to label the nine specific technologies as NGDTs to avoid this pitfall and also facilitate concise analysis within this paper.

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the future, and the ways in which firms will use these technologies (Kagermann et al., 2011; Schwab, 2016; Marr, 2016). Among the notable findings in the literature is the predicted interconnectedness of NGDTs for data collection and automated decision making. These technologies are expected to impact both the economy and society in a myriad of ways, from labor markets to global value chains (OECD, 2017a). Recently, researchers have begun examining the use and performance effects of NGDTs. Unlike earlier forecasts on the interconnectedness of these technologies, much of the current work examines these tools in isolation (DeStefano and Timmis, 2021; Sestino et al., 2020; Greenstein and Fang, 2020; Acemoglu et al., 2020; DeStefano et al., 2020a,b; Candi and Beltagui, 2019; Beltagui et al., 2020; Graetz and Michaels, 2018).

While there has been significant research in this area, a few important gaps remain. First, there is little information relating to the types of businesses that are using these technologies. Next, there is the question of whether they are being employed in isolation, or in bundles. Answering these questions will help provide essential insights to managers weighing whether to use these new technologies, and to policy makers attempting to create market environments which facilitate technology diffusion. Until recently, data quality on the diffusion of NGDTs was poor.[4] Previous surveys typically had limited coverage (OECD, 2019a) and some technologies — including AI, until recently — even lacked a universally recognized definition (OECD, 2019b).

To answer these questions, this paper relies on a novel and relatively unused dataset collected by the National Statistical Office of Korea (KOSTAT), the Survey of Business Activities. The survey introduced new questions on NGDT use in the year 2018 (reporting year 2017) for the explicit purpose of understanding the extent to which firms in South Korea were using NGDTs. Firms were surveyed on their use of IoT, mobile devices, data analytics, cloud computing, AI, blockchain, virtual/augmented reality, industrial robotics and 3D printing technologies. This paper uses a suite of methodological techniques, including descriptive statistics and regression analysis to understand the diffusion of these technologies, and to assess the relationships between use and various firm attributes.[5]

This paper will attempt to answer the following two questions:

- Which firm characteristics determine the use of NGDTs?
- Are firms using these technologies in isolation or in bundles?

We are motivated to answer these questions for a number of reasons. First, the use of new technologies is important for a firm to gain competitive advantage, and for its implementation of innovative processes at the micro-level (Jin and McElheran., 2018; Cardona et al., 2013; Brynjolfsson and McAfee, 2014; Bloom et al., 2012; Syverson, 2011), and to evaluate economic growth disparities at the macro-level (Niebel, 2018; Fernald, 2014; Timmer et al., 2011; O'Mahoney et al., 2008). Second, the ability to use emerging technologies to grow is an important driver for economic development and wealth creation in any economy, especially for entrepreneurs and young firms (Criscuolo et al., 2014, Calvino et al., 2016; Henderson, 1993; Tushman and Anderson, 1986).[6] Third, NGDTs are expected to profoundly impact the economy, disrupting the way firms compete and organize now, and in the near-future (Brynjolfsson and McAfee, 2014; Agrawal, Gans and Goldfarb, 2018; McElheran, 2018; Agrawal et al., 2019; Goldfarb et al., 2020; Iansiti and Lakhani, 2020). Lastly, NGDTs may lead to concentrated job losses (Acemoglu et al., 2020; Acemoglu and Restrepo, 2020; Silva et al., 2019; Frey and Osborne, 2017; Brynjolfsson and McAfee, 2014) and widening income inequality (Bessen et al., 2021; Van Reenen, 2011; Aghion et al., 2002). History has set the precedent for the future, providing countless examples of social upheaval that coincide with economic transitions driven by technology (Fischer, 1966; Foster, 2003; Berlanstein, 1992).

The remainder of the paper is arranged as follows. Section 2 reviews and analyzes the literature, while elucidating the hypotheses. Section 3 discusses the data, while Section 4 lays out the econometric strategy. Descriptive statistics on the diffusion of NGDTs are presented in Section 5, and the empirical results are discussed in Section 6. Section 7 summarizes the paper and suggests areas of consideration for managers, policymakers and future researchers.

2. Literature review and theoretical predictions

The following paper makes contributions to two different bodies of literature, notably on digital technology diffusion and technology complementarities. Each of these are discussed in detail below.

2.1. Digital technology diffusion

There exists a surplus of well-established literature on the determinants of digital technology use. Specifically, studies using firm-level data have shown that certain types of firms exhibit increased propensities of technology adoption over others. Traditional digital technologies are especially large-firm biased. Large firms are likely to have more knowledge-based capital and more accumulated technology, making it easier for them to adopt emerging technologies (Gibbs and Kraemer, 2004). The use of modern technologies by large firms may have triggered dynamics that have benefitted a minority of leading frontier firms, further widening disparities across businesses (Calvino et al., 2016; Brynjolfsson et al., 2008).[7] For example, enterprise resource planning (ERP) software is attractive to large multinational entities, as it allows them to coordinate and profit from substantial production networks (OECD & World Bank, 2015).

Being classified as a young firm has also been identified as a relevant determinant of technology use. Theoretically, young firms are likely to have newer assets, which are often more compatible with newer technologies (Baldwin and Rafiquzzaman, 1998).[8] Haller and Siedschlag (2011) find that young firms that experience rapid growth have a greater probability of owning a website. Similarly, DeStefano et al. (2017) find that younger firms are more likely to adopt certain types of hardware over older firms. On the other hand, Luque (2000) suggests that young firms are more likely to adopt emerging technologies while they are still small.

The literature also documents several important relationships between innovation and technology use. The literature has typically found that investments in R&D correlate with new digital tools (Giotopoulos et al., 2017; Alshamaila et al., 2013; Marcati et al., 2008; Giunta and Trivieri, 2007; Hollenstein, 2004; Lal, 1999). Innovation outcomes have been linked with technological diffusion, which several studies in the journal, Technovation have highlighted. In parts of Europe, research has

[4] Governments and governing organizations have, in a limited fashion, conducted surveys on NGDT use (Byrne and Corrado, 2017; Byrne et al., 2018; Brynjolfsson et al., 2018). Examples include the US Census Bureau (Zolas et al., 2020) and the German Community Innovation Survey (Rammer et al., 2021).

[5] To our knowledge, this is the first paper to use questions on NGDTs use from the KOSTAT dataset.

[6] This is relevant in light of the recent slowdown of business dynamism (Crafts and Mills, 2020; Bajgar et al., 2020; Decker et al., 2016; Calvino et al., 2015).

[7] At the same time, large firms typically employ significant amounts of incumbent assets and practices in the form of legacy software and siloed data practices, which can make it challenging to adopt new data collection methods and AI that typically require decentralized data centers either internally or via the cloud (Bommadevara et al., 2018; Iansiti and Lakhani, 2020).

[8] However, older firms may have greater amounts of accrued know-how, potentially allowing them to adopt and exploit advanced technology more effectively than young firms (Arvanitis and Hollenstein, 2001).

established a clear relationship between product and service innovation, and digital technology deployment (Blichfeldt and Faullant, 2021). In the U.S., a survey of managers revealed that 3D printing can springboard innovation and boost firm performance (Beltagui et al., 2020). Emerging technologies benefit from holistic roadmaps. This indicates that strategic frameworks for technology facilitate specific system approaches that are more apt to adopt and increase innovative activities (Featherston et al., 2016).

The diffusion of frontier digital technology corresponds with firms becoming increasingly more reliant on assets like data; highlighting the significance of intangible investments in new digital technologies (Haskel and Westlake, 2017; Byrne and Corrado, 2017; Byrne et al., 2018; Andres et al., 2020; DeStefano et al., 2020a,b). Firms that are foreign-owned typically exhibit increased levels of productivity and technology utilization (López-Acevedo, 2002; Griffith et al., 2002). Foreign direct investment literature finds extensive evidence of knowledge spillovers from foreign multinational entities (Javorcik, 2004; Havránek and Iršova, 2011). Multinationals often require and uphold strict productivity and production standards, and may therefore readily share new technologies throughout the firm (Criscuolo and Timmis, 2017).

To summarize, the literature identifies several attributes important for the adoption of NGDTs, which we define as "firm characteristics." These represent size, productivity, R&D activity, intangible intensity, being young and being owned by a foreign firm. The importance of these characteristics for technology adoption motivates us to assess both their role, and impact on NGDTs, and are therefore included as independent variables in our econometric analysis. In doing so, we test the following hypothesis:

Hypothesis I. Firm characteristics positively predict the use of any NGDT

2.2. *Use in bundles or isolation*

To our knowledge, the usage of NGDTs occurring either in isolation or in bundles has not been extensively researched.[9] While empirical studies typically focus on the determinants and performance effects of a single technology (Cardona et al., 2013), the reality is, firms likely rely on technologies in bundles. In this study, bundling refers to the use of any two, or more technologies simultaneously. Digital tools generally work together serving various functions, such as creating, collecting, and exploiting large sums of data (Goldfarb et al., 2020; McElheran, 2018; Sestino et al., 2020). For example, firms wanting to use AI require large datasets to train their algorithms, which can be generated and collected at scale using IoT and big data practices. These can then be processed and stored on cloud computing services (Iansiti and Lahkani 2020; DeStefano et al., 2020a,b; OECD, 2019a). In addition, classes of technologies that impact productivity, quality, and flexibility of goods production, including, robotics, Computer-aided Design/-Computer-aided Manufacturing (CAD/CAM) software, and 3D printers, serve as important complements to each other within manufacturing processes (Graetz and Michaels, 2018; De Backer et al., 2018; DeStefano and Timmis, 2021).

While likely evident to practitioners, most high-income countries design economic policies that either encourage the use of one particular technology, or target capital investments more generally, excluding technology acquired through services (Tax Foundation, 2018). This has been found to discourage firms from adopting cloud computing and data analytics (Andres et al., 2020). As discussed above, while NGDTs are assumed to be implemented in bundles, this has to our knowledge, not been empirically tested. Understanding the extent of NGDT bundling is relevant to managers looking to invest in new technologies, and is also useful for policy makers that design regulatory frameworks for appropriate technology adoption. Consequently, in this paper we examine the extent to which these technologies are being used simultaneously.

There is a new and growing body of work which examines the nature and use of NGDTs, typically assessing the use of these technologies individually, rather than in bundles. This research covers many of these new technologies including, big data (OECD, 2017b; Urbinati et al., 2019; Andres et al., 2020; Sestino et al., 2020), IoT (Sestino et al., 2020), cloud computing and data centers (Greenstein and Fang, 2020; DeStefano et al., 2020b; Jin and McElheran, 2018; Etro, 2015; OECD, 2015), 3D printing (Candi and Beltagui, 2019; Beltagui et al., 2020), AI (Kinkel et al., 2021; Goldfarb et al., 2020; Zolas et al., 2020), blockchain (Queiroz and Wamba, 2019; Akgiray, 2019) and robotics (DeStefano and Timmis, 2021; Acemoglu et al., 2020; Graetz and Michaels, 2018). We contribute to this growing body of work by providing a comprehensive empirical analysis of the usage of NGDTs, and the likely parallels between them. In doing so we test the following hypothesis:

Hypothesis II. Firms are bundling NGDTs rather than using them in isolation

3. Data

This paper relies on firm-level data collected by the Survey of Business Activities from Statistics Korea (KOSTAT). Since 2005, KOSTAT has conducted surveys to provide comprehensive data on business activities, such as firm performance, systematization, diversification and management systems. Surveys are conducted either by in-person visitations, or online-based questionnaires that are then supplemented with administrative data and other pertinent business information. The survey is inclusive of all corporations having at least 50 full-time employees, and capital stock valued at KRW 300 million (equivalent to roughly USD 250,000) or more — encompassing approximately 13,000 firms from various industries.[10]

In 2018, KOSTAT included questionnaires on the use of NGDTs to assess which firms used these emerging digital tools in 2017 (notably IoT, mobile devices, big data, cloud computing, AI, blockchain, virtual/augmented reality, robotics and 3D printing). Expert debate and discussion led to the identification of these nine technologies as the core technologies that will facilitate future economic revitalization. The objective of KOSTAT is to enable researchers and policymakers to assess the business environment in South Korea, in order to develop coherent economic policies to encourage further technology use. The inclusion of the NGDT questions enables researchers to examine the extent to which firms are using these technologies and to gauge whether the economy is technologically upgrading. Their respective definitions can be found in Table 1.

4. Empirical strategy

The objective of the empirical strategy is to test the hypotheses discussed in Section 2. The analysis uses a model that takes into account the relationship between use of NGDTs and firm characteristics. Based on the theoretical predictions of the literature discussed in Section 2, we define firm characteristics to include size, R&D intensity, intangible intensity, productivity, being young, and foreign ownership. The use of NGDTs, the dependent variable, is a binary response of 0 or 1. Therefore, we estimate the probability of whether a firm employs NGDTs with an

[9] The term complementarity comes from microeconomics theory which defines a phenomenon where the demand of a particular product is linked to the demand of another (Carbaugh 2006).

[10] Note that enterprises in wholesale and retail trade and other service industries, enterprises with fewer than 49 full-time employees are included in the sample if their capital stock is valued at one billion KRW or more.

Table 1
Definition of next generation digital technologies.

Technology type		Definitions
Internet of Things (IoT)		Smart sensors and devices communicate information between people and things by connecting all objects via the Internet. (OECD, 2017b).
Cloud Computing		Cloud computing is a service delivered by third-party providers that "enables pay as you go on-demand network 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" (NIST, 2011)
Big Data		The practice of collecting, processing, and analyzing large volumes of digital data on a massive scale may include numerical, text, and image data (both structured and unstructured) (OECD, 2017b).
5G		The next-generation mobile technologies and services being deployed (5G).
AI		A technology that enables machines to become intelligent, including the ability to learn, deduce, perceive, and understand natural language through computer programs, to perceive, analyze, determine response and act appropriately in their environment. For a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments (OECD, 2019b).
Blockchain		An "open, distributed ledger that can record transactions between two parties efficiently and in a verifiable and permanent way" (Iansiti and Lakhani, 2017).
3D Printing		3D printing technology uses digital files to build physical three-dimensional objects with hard materials such as plastics by successively adding layers of material until the model is complete (OECD, 2017a).
Robotics		A machine that can be reprogrammed that is multipurpose in function, allows for physical alteration, and is mounted on an axis (IFR, 2017)
Virtual and Augmented Reality (VR, AR)	**VR**	A technology that creates virtual images of objects, backgrounds and environments (OECD, 2020b).
	AR	A technique that creates a single image through overlapping three-dimensional virtual images onto actual backgrounds or images (OECD, 2020b).

Source: Statistics Korea (2018b). Report on the 2017 Survey of Business Activities.

equation using Probit as well as Ordinary Least Squares (OLS).[11],[12] The definitions for these variable can be found in Table 2.

The model specified in equation (1) will be used to test Hypothesis I.

$$y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \tag{1}$$

y_i is the dependent variable, which is a binary variable that identifies the use of any of the NGDTs for firm (i). β_1 is the covariance matrix of parameter estimators, which refers to the relationship between the firm's characteristics (X_i). (X_i) refers to a vector of covariates including, (log) total sales and (log) number of employees representing size, the share of R&D investment over total sales as R&D intensity, the share of intangible assets over total assets depicting intangible intensity, and (log) value-added per worker referring to labor productivity. Young firms are reflected as a dummy variable which equals 1 if the firm is five years old or less as of 2017, and 0 otherwise. Finally, firm foreign ownership is reflected by a dummy variable equal to 1 if the share of foreign assets is greater than fifty percent, and 0 otherwise.[17] ε_i represents the error term, and given the level of analysis, regressions are clustered at the firm level.

The model specified in equation (2) will be used to test Hypotheses II.

$$y_{ik} = \beta_0 + B_1 Y_{ik(-1)} + B_2 X_i + \varepsilon_i \tag{2}$$

y_{ik} is a binary variable representing the use of NGDT (k) by a firm. If firm (i) employs a technology (k), the variable is equal to 1; if not, it is 0. $Y_{ik(-1)}$ is an indicator matrix that describes the usage of the other eight different technologies, except for technology k by firm (i) with a dummy variable matrix. The remainder of the model is consistent with Equation (1).

First, we estimate the relationship between firm characteristics and the use of NGDTs in equation (1) using OLS and Probit. Given the consistency in the results between the estimation strategies, the remainder of the paper relies solely on Probit, since the outcome variables are binary (Wooldridge, 2016).

5. Descriptive statistics

Among the 12,579 firms in the sample, 1014 (8%) employed one or more NGDT in 2017 (See Fig. 1), which we subsequently termed, advanced-technology using firms (ATUFs). While this number may appear to be on the lower side, the deployment of many of these technologies has only recently begun, and this proportion is in line with statistics from U.S. firms (Zolas et al., 2020).

Table 2
Variables for firm characteristics.

Firm Characteristic	Variable
Size	Log (total sales)
	Log (total number of employees)
R&D intensity	R&D investment/total sales
Intangible intensity	Intangible assets/total assets
Productivity	Log (value-added/total number of employees)
Young status	1: if the firm≤5 years old
	0: otherwise
Foreign ownership	1: if the share of foreign assets>50%
	0: otherwise

Note: Each variable is calculated by the authors based on the raw data provided by the KOSTAT survey.

Considerable variation in the use of NGDTs exists across industries (see Fig. A1 in the Appendix). Of the 1014 users of NGDTs, the sector most reliant on these technologies is the Information Communication Technology (ICT) sector, where 25.3 percent of firms use at least one of these new technologies. This is followed by the Financial and Insurance sector, where 15.9 percent of firms use at least one NGDT.[13] In contrast, amongst manufacturing firms, only 6.7 percent of firms used one or more of these new technologies. Proportionally speaking, Daejeon, Kangwan, and Seoul exhibit the highest percentage, 33% for regions in South Korea (as seen in Fig. A2 in the Appendix).

There are considerable differences in the usage of these different technologies. Mobile 5G is the most widely used at 22%, followed by big data and cloud computing at 17% (Fig. 2). On the other hand, roughly 5% of firms used AR and VR, robotics, and blockchain technologies. Another interesting finding is the extent to which firms are using multiple technologies. Fig. 3 illustrates the proportion of firms and the number of advanced technologies used. About half of the ATUFs use more than a single technology simultaneously, while close to a quarter use three technologies or more. These statistics highlight that a considerable number of firms are employing these technologies in

[11] Wooldridge (2016).

[12] To control for any potential time invariant variation across industries and regions, the regressions include two-digit industry (Korean Standard Industry Classification) and regions (state-level) fixed effects.

[13] Sector definitions are derived by Korean Standard Industry Classifications (KSIC).

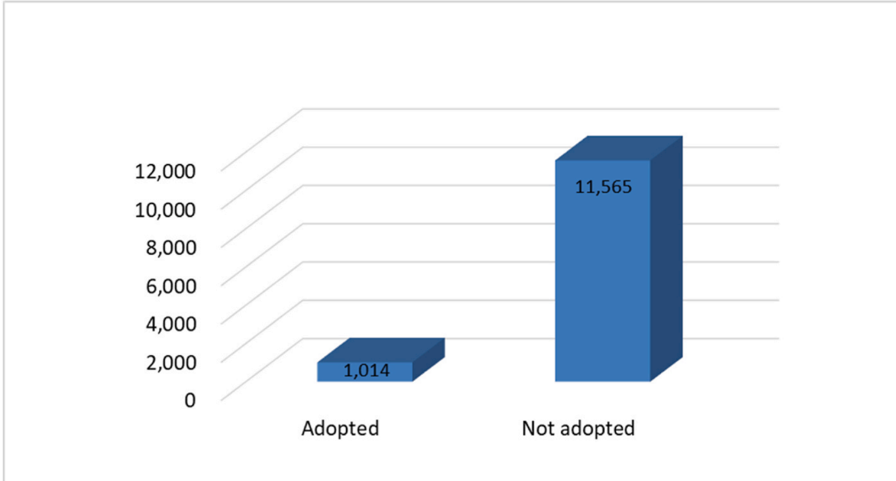

Fig. 1. Ngdt usage by firms (total).
Source: Statistics Korea (2018a). Survey of Business Activities (reference year: 2017).

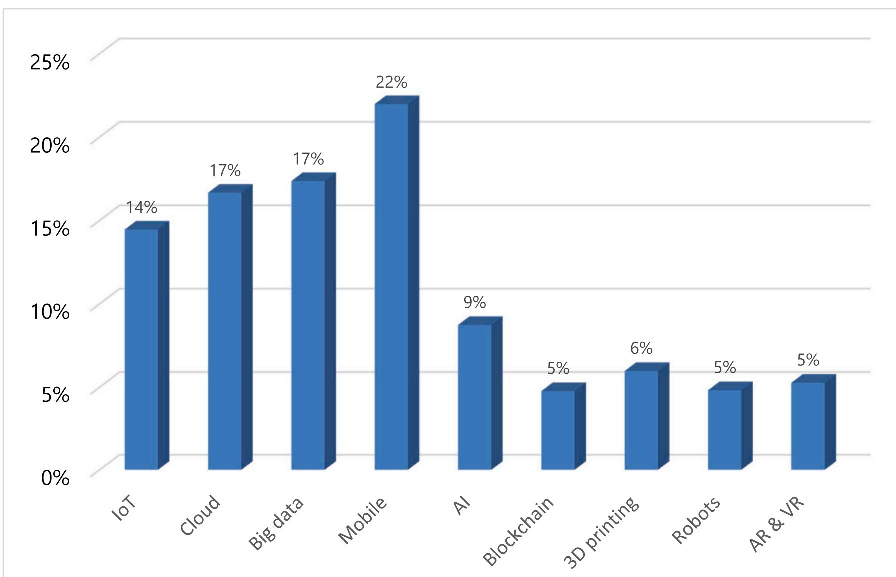

Fig. 2. Proportion of firms using NGDTs, by technology (multiple types allowed).
Source: Statistics Korea (2018a). Survey of Business Activities (reference year: 2017).

bundles, which appears to validate our hypothesis.

Fig. 4 provides a matrix of the number of firms using a combination of at least two selected technologies. The 5G-big data combination is the most common, with 175 firms actively employing this combination. The following combinations of advanced technology utilization have been observed in the order of frequency: 5G-cloud, big data-cloud, AI-big data, and AI-5G. These combinations of technology deployments appear consistent with their functionality, and consistent with the findings of Goldfarb et al. (2020). For example, 5G and IoT tend to generate large sums of data, while cloud computing is an effective tool to store and process this information. Furthermore, AI is most effective when firms leverage big data to train and improve the accuracy of their algorithms.

Note: The size of the circle corresponds with the number of firms that have used a technological dyad. A bigger circle represents more firms.

Source: Statistics Korea (2018a). Survey of Business Activities (reference year: 2017).

6. Empirical results

6.1. Question one: which firm characteristics determine the use of NGDTs?

This study affirms previously conducted research on usage and adoption of digital technologies for business (Bresnahan et al., 2002; Gibbs and Kraemer., 2004; Giunta and Trivieri, 2007; Haller and Siedschlag, 2011; DeStefano et al., 2018; OECD & World Bank, 2015; Haskel and Westlake, 2017). Table 3 shows that all variables except for R&D intensity (in OLS) regarding firm characteristics are statistically correlated with the use of any NGDT. This result mostly supports Hypothesis I.

First, our analysis shows that after analyzing firm characteristics, larger firms are more likely to employ an NGDT. Both total sales and the number of employees are positively associated with the use of at least one NGDT. The positive relationship between technology use and being young is also consistent with previous research on traditional digital

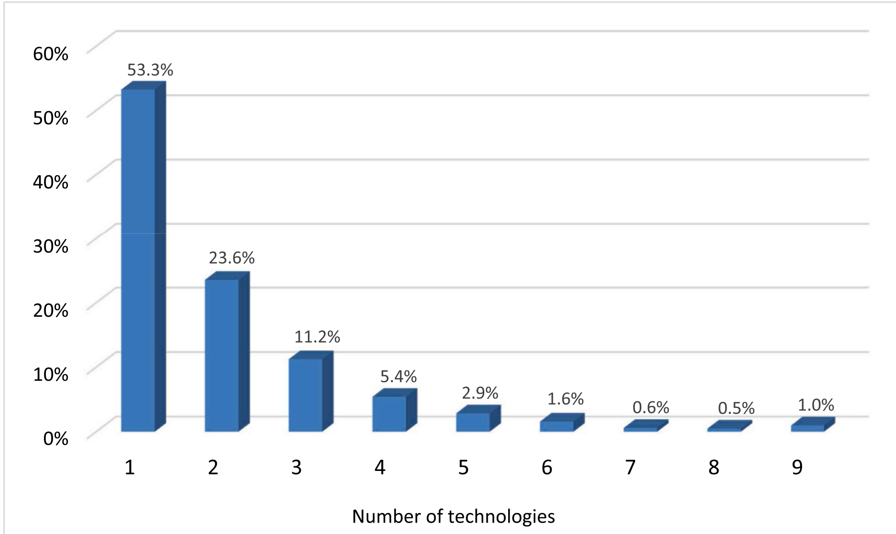

Fig. 3. Proportion of firms that use one or more NGDT
Source: Statistics Korea (2018a). Survey of Business Activities (reference year: 2017).

	IoT	Cloud	Big data	Mobile	AI	Blockchain	3D printing	Robots	AR & VR
IoT		102	110	111	65	41	30	34	48
Cloud	102		153	154	80	49	27	31	45
Big data	110	153		175	114	58	33	37	56
Mobile	111	154	175		84	51	32	35	58
AI	65	80	114	84		41	23	32	39
Blockchain	41	49	58	51	41		12	20	22
3D printing	30	27	33	32	23	12		24	20
Robots	34	31	37	35	32	20	24		21
AR & VR	48	45	56	58	39	22	20	21	

Note: The size of the circle corresponds with the number of firms that have used a technological dyad. A bigger circle represents more firms.

Fig. 4. Summary of relationships between technology dyads.

technologies (Haller and Siedschlag, 2011; Oliveira et al., 2014; Ohnemus and Niebel, 2016; OECD, 2020a). In general, larger firms appear to have a comparative advantage in generating returns on innovation activities and considerable resources to leverage new technologies. Young firms on the other hand are more likely to employ advanced technologies potentially as a result of less rigid organizational structures and newer capital stock (Baldwin and Rafiquzzaman, 1988), or because they are more willing to take innovative risks (Coad et al., 2016).

The use of intangible assets appears to be a strong determinant of NGDT use, a finding that is consistent with Haskel and Westlake (2017). More productive firms also exhibit a greater likelihood of using NGDTs, which corresponds with the literature on previous digital technologies

Table 3
Determinants of NGDT use by firms.

Dependent variable: NGDT use	(1)	(2)
Estimation Method:	OLS	Probit
Log sales	0.013***	0.100***
	[0.004]	[0.026]
Log employment	0.033***	0.171***
	[0.005]	[0.034]
Young (5 years old<=)	0.029*	0.176**
	[0.017]	[0.089]
R&D intensity	0.124	0.457*
	[0.089]	[0.259]
Labor productivity	0.009***	0.039*
	[0.003]	[0.020]
Share of intangible assets	0.072***	0.440***
	[0.017]	[0.086]
Foreign-owned	−0.029***	−0.153**
	[0.009]	[0.070]
Observations	10,604	10,499
R-squared	0.094	N/A

Note: Young is defined as a firm five years old or less as of 2017. R&D intensity is the share of R&D expenditure out of total sales and the share of intangible assets is the share of intangible assets over total assets. Labor productivity is value-added per worker. To control for any potential time invariant variation across industries and regions, the regressions also include two-digit industry (Korean Standard Industry Classification) and regions (state-level) fixed effects. A few observations are dropped in Probit due to variables that predict failure perfectly in STATA. Robust standard errors clustered at the level of the firm in brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Regressions reflect the year 2017.

(Syverson, 2011; Bloom et al., 2014). Although less concrete, more R&D active firms use NGDTs, albeit only at the 10% level of significance in the Probit estimation and a positive coefficient yet insignificant in the OLS estimation. This does not diminish the importance of firm innovation on NGDT use, especially given that R&D is only one way to measure innovation (as an input as opposed to an output, say by patent applications or new product/service interventions). Unfortunately, our dataset does not provide us with additional metrics for innovation.

One new finding that this investigation has yielded is that foreign firms are less likely to employ these technologies when compared to domestic firms. In general, foreign firms are widely perceived as superior to their domestic counterparts in various aspects, and often possess new technologies, and achieve greater gains from these (Bloom et al., 2012). However, the analysis presented compares domestic firms, mostly the headquarters of multinational corporations, and foreign firms, mostly subsidiaries. Previous studies have found that headquarters exhibit higher ICT usage levels than branch offices (DeStefano et al., 2017), which potentially explains the negative correlation we find between foreign ownership and NGDT use.

Overall, the results suggest that the use of an NGDT is biased towards large and young firms that exhibit both high productivity and use intangible assets. While this is consistent with the use of previous digital technologies, what remains unclear is whether these characteristics matter, and if so, how impactful these are for each of these technologies. It is possible that some of the technologies are simply more applicable to smaller firms, such as cloud computing (Bloom and Pierri, 2018), and have less to do with size, productivity, or asset use.

6.2. *Question two: are firms bundling NGDTs, or are they using them in isolation?*

The results in Table 4 show statistical complementarities across a considerable proportion of NGDTs. These results support Hypothesis II, which posits that firms are using NGDTs in bundles rather than in isolation. One takeaway is that the usage of technologies that require data (such as AI) are accompanied by technologies that generate large amounts of information (such as 5G, IoT, and big data), and facilitate its storage and processing (cloud computing). The cloud in and of itself enables the storing and processing of information with more flexibility, facilitating the use of big data, IoT, and 5G. These complementarities between cloud computing, internet technologies and big data are consistent with previous research (DeStefano et al., 2020a,b). The combination of computing and storage power, and large sums of data

Table 4
Complementarities between NGDTs.

	1	2	3	4	5	6	7	8	9
Dependent variable:	IoT	Cloud	Big data	5G	AI	Blockchain	3D printing	Robots	AR & VR
Estimation method:	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit
IoT		0.724***	0.824***	0.741***	0.313*	0.340	0.399**	0.559***	0.656***
		[0.140]	[0.133]	[0.141]	[0.184]	[0.231]	[0.202]	[0.207]	[0.158]
Cloud	0.722***		1.079***	1.126***	0.391**	0.120	0.200	0.184	0.090
	[0.135]		[0.124]	[0.122]	[0.155]	[0.228]	[0.218]	[0.258]	[0.199]
Big data	0.744***	1.029***		1.056***	1.359***	0.950***	0.407*	0.540**	0.531***
	[0.133]	[0.122]		[0.120]	[0.150]	[0.201]	[0.239]	[0.248]	[0.177]
5G	0.766***	1.148***	1.057***		0.354**	0.684***	0.513**	0.464**	0.783***
	[0.124]	[0.111]	[0.108]		[0.151]	[0.185]	[0.201]	[0.187]	[0.156]
AI	0.256	0.296*	1.368***	−0.074		0.375*	0.343	0.664**	0.409*
	[0.183]	[0.168]	[0.176]	[0.202]		[0.220]	[0.282]	[0.274]	[0.216]
Blockchain	0.359	0.169	0.921***	0.301	0.394*		0.160	0.557*	0.373
	[0.247]	[0.219]	[0.271]	[0.258]	[0.228]		[0.374]	[0.292]	[0.252]
3D printing	0.583***	0.131	0.550**	0.602**	0.477*	0.35		0.962***	0.678**
	[0.206]	[0.249]	[0.273]	[0.241]	[0.285]	[0.421]		[0.198]	[0.272]
Robots	0.675***	0.248	0.805***	0.637***	1.129***	0.780**	1.005***		0.490
	[0.234]	[0.272]	[0.257]	[0.232]	[0.267]	[0.346]	[0.201]		[0.299]
AR & VR	0.678***	0.071	0.537**	0.627***	0.527**	0.257	0.551**	0.204	
	[0.196]	[0.221]	[0.252]	[0.238]	[0.239]	[0.282]	[0.273]	[0.288]	
Control variables									
Firm characteristics	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	9526	9542	10,030	10,103	7112	5403	7286	6989	6522

Note: Robust standard errors clustered at firm in brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Regressions reflect the year 2017. Additional firm controls are all the firm explanatory variables used in the baseline estimation, including Young is defined as a firm five years old or less as of 2017, log sales, log employment, R&D intensity, log labor productivity, the share of intangible assets and foreign ownership. To control for any potential time invariant variation across industries and regions, the regressions also include two-digit industry (Korean Standard Industry Classification) and regions (state-level) fixed effects A few samples are dropped for each estimation in Probit due to variables that predict failure perfectly in STATA.

appears to be an important requirement for AI use, which is also consistent with Goldfarb et al. (2020). The results likewise indicate strong complementarities between robotics, 3D printing, and data-intensive technologies such as IoT, big data, 5G mobile, and AI. The pairing of industrial equipment with data collection practices, advanced software and telecommunications suggests the importance of bundling data and intangibles (Haskel and Westlake, 2017) in the production process. Overall, our analysis importantly captures technology bundling that are consistent with their functionality, as opposed to an overall increase in technology use by firms in our data.

7. Conclusion

The diffusion of new digital technologies such as AI, IoT, big data and 3D printing is expected to have economic and social implications. Despite the prevalence of anecdotal evidence, there are limited empirical studies on the extent to which these technologies are being used by businesses. Using novel firm-level data from South Korea, our research attempts to answer the following questions: (1) What types of firm characteristics determine the use of any of the NGDTs? (2) To what degree do firms use these technologies in bundles?

Our analysis suggests that firm size, labor productivity, investments in intangible assets and being young are strong predictors of NGDT use in general, consistent with the use of more traditional digital tools. The research also demonstrates that firms are not embedding these technologies in isolation. Among the firms that use these technologies, a considerable percentage employ two or more technologies simultaneously. Assessing this further, technologies that require and facilitate the use of large datasets, such as AI and cloud computing, are statistically linked with practices that generate large amounts of data (i.e., IoT, 5G and big data). In addition, there are complementarities in the use of robotics and data-intensive practices such as IoT, big data and AI, suggesting that the combination of data and industrial equipment is perceived by firms to be important for production.

The simultaneous use of multiple technologies is an essential determinant driving a firm's decision to acquire any one technology. The resulting pattern highlights the need for researchers to exercise care when analyzing single technology usage because of a possible omitted variable bias. Unobservable factors outside of a standard firm's characteristics are also important and can be significant. The results provide insights to managers who decide to use these advanced technologies and make investments in human capital and R&D (Frederick et al., 2018; Liang and Goetz, 2018). Furthermore, the results suggest that policymakers need to encourage the adoption of multiple technologies rather than incentivizing the use of one particular technology. Firms use a variety of technology combinations that are both available as services and through investments, which suggests that traditional policy tools such as capital incentive programs (targeting investments in physical capital) may have unexpected outcomes.

The newness of these results is an inherent limitation to the conclusions drawn. Multiple years of data would enable us to employ various techniques (such as first differencing or diff-in-diff methods) to control time invariant factors which may also explain NGDT use — and that would help reaffirm our results. We hope to carry out further analysis in this area once additional time series data become available.

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Appendix

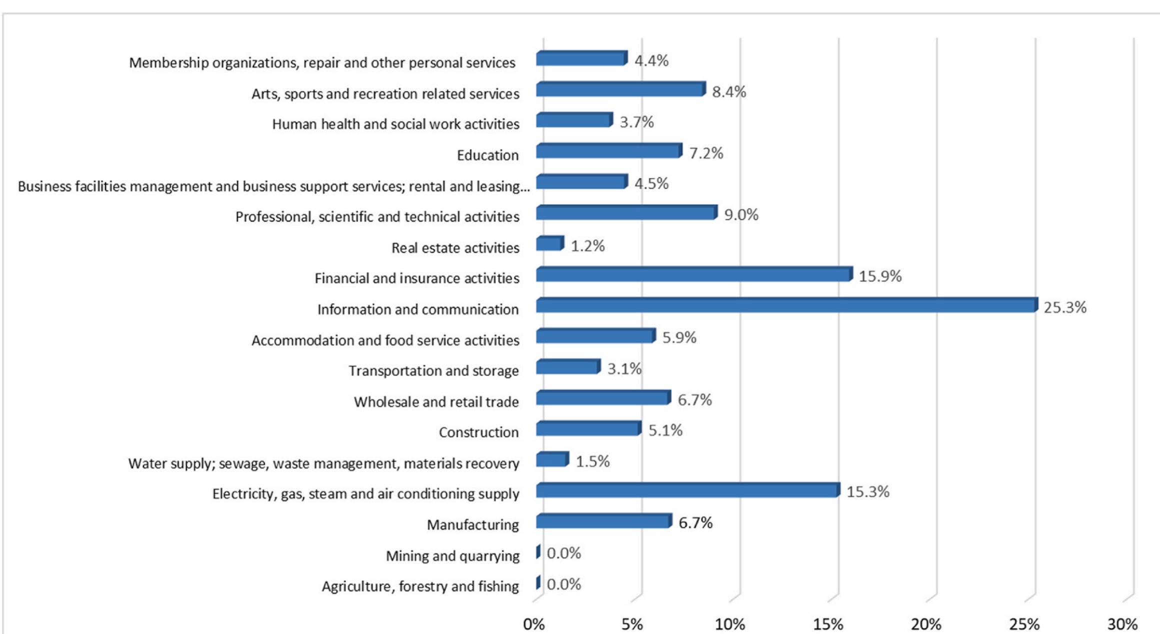

Fig. A1. Proportion of Firms Using NGDTs, by Industry.Source: Statistics Korea (2018a). Survey of Business Activities (reference year: 2017).

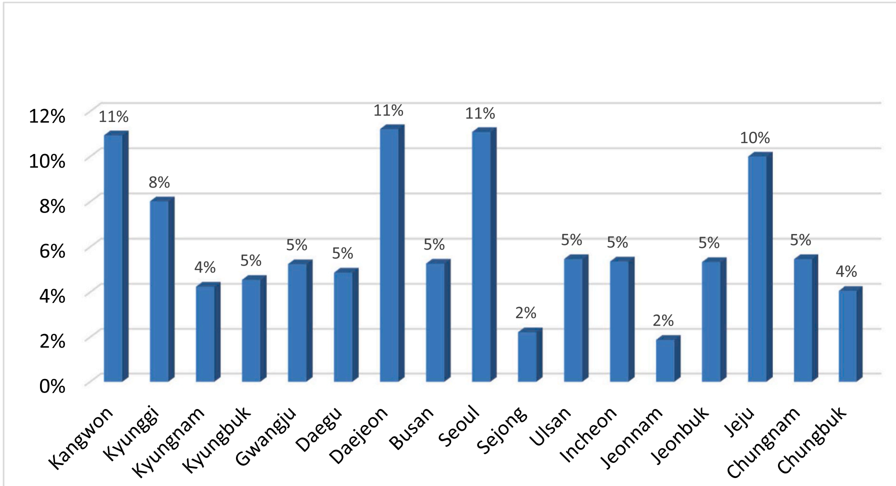

Fig. A2. Proportion of Firms Using NGDTs, by Region.Source: Statistics Korea (2018a). Survey of Business Activities (reference year: 2017).

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