Technology adoption and upskilling in the wake of Industry 4.0

Luca Grilli, Mattia Pedota*, Lucia Piscitello

Politecnico di Milano, Department of Management, Economics, and Industrial Engineering
Via R. Lambruschini 4b, 20156, Milan, Italy

*corresponding author: mattia.pedota@polimi.it

Abstract

Understanding how Industry 4.0 technologies complement each other on one side, and human skills on the other is becoming an increasingly important research concern. However, firm-level evidence on patterns of conjoint adoption of Industry 4.0 technologies and upskilling is still scant. The present work aims to cover this gap by leveraging a large cross-sectional database of Italian firms. Our analysis reveals two distinct patterns of conjoint adoption, reflected in the propensity to adopt digital I4.0 technologies on the one hand and the propensity to adopt physical I4.0 technologies on the other. Despite directing investments toward well-defined subclusters of I4.0 technologies, the two propensities are not mutually exclusive. Furthermore, not only the digital adoption propensity, but also the physical one increases the likelihood of the firm upgrading the ICT skills of its ICT-specialized and non-ICT-specialized employees conjointly. This result holds for medium and large firms, whereas small firms constitute an interesting exception, calling for further research on the topic.

1. Introduction

The Industry 4.0 (I4.0) phenomenon, often identified with the Fourth Industrial Revolution, is currently at the center of academic, managerial and institutional debates (EPO, 2017; OECD, 2017; Sung, 2018). Despite lacking a unique definition and a shared set of boundaries, it generally refers to the conjoint firm-level implementation of advanced digital and automation technologies like artificial intelligence, augmented reality, big data analytics, cloud computing, the internet of things, robots and 3D printing. Taken together, these technologies enable automation, flexibilization, human-machine interconnectivity and mass customization, leading to the emergence of innovative business models and smart factories (Kagermann, 2015; Osterrieder et al., 2020), with new skill requirements and far-reaching effects on the labor market (Frey and Osborne, 2017) and the international competitive landscape (Strange and Zucchella, 2017).

I4.0 technologies display remarkable dynamism and complementarity, but they have yet to become fully-fledged general purpose technologies, and their conjoint evolutionary pattern is still rather unpredictable (Martinelli et al., 2021). Although patent data indicate a general trend of convergence (EPO, 2017), it is still difficult to discern which I4.0 technological trajectories are truly interdependent and likely to form aggregate technological paradigms (Dosi, 1982; Pedota et al., 2021). In such a dynamic context, the ability by firms to benefit from the ongoing revolution requires skillful adaptation from a variety of perspectives. The mere adoption of I4.0 technologies may be a necessary but certainly not a sufficient condition to become competitive within the emerging paradigms. To this end, firms also need to anticipate the coevolution of I4.0 technological trajectories (Ciarli et al., 2021), reorganize factories and employees (Calabrese et al., 2020), improve coordination across organizational units (Horvath and Szabo, 2019), gather sufficient know-how (Cugno et al., 2021), overcome organizational resistance (Birkel et al., 2019) and endow themselves with complementary human skills (Kiel et al., 2017; Muller et al., 2018).

The latter factor is particularly important. Instantiations of I4.0 may be framed as sociotechnical systems, where technologies and workers are complementary and interdependent (Neumann et al., 2020). However, more information on the characterization of such systems is needed. Although extant literature is almost unanimous in regarding I4.0 technologies as mutually complementary and the upskilling of human resources as a necessary step to reap their benefits, a fine-grained empirical analysis on this matter is missing. The I4.0 technological cluster is assumed to require new specific skills like statistical proficiency and data/information processing (Karre et al., 2017), as well as broader skills like sociability (Ciarli et al., 2021) and creativity (Pedota and Piscitello, 2020), but several issues remain relatively unexplored. First, clearer boundaries should be set within the broad I4.0 cluster, based on technological characteristics, epistemological trends and adoption patterns. Second, based on extant evidence it is difficult to ascertain whether it is I4.0 as a whole that requires an upskilling of the workforce or, rather, a subcluster of technologies within it. Third, it is unclear whether I4.0 technologies require a selective upskilling only of a part of the workforce, or a more holistic upskilling. Fourth, while some works imply that small firms may be impaired in their ability to benefit from I4.0 (e.g. Horvath and Szabo, 2019; Zolas et al., 2021), we lack a comprehensive view on the extent to which firm size plays a role in the adoption of different I4.0 technologies and the related upskilling of the workforce.

The present work contributes to covering these gaps by leveraging the “survey on information and communication technology usage in enterprises - year 2018”, a cross-sectional database of 21,934 Italian firms taken from the Italian National Institute of Statistics (ISTAT). The database includes information about firm-level investments in six key I4.0 technologies, namely augmented reality, big data analytics, cloud computing, the internet of things, robots and 3D printing, and it also indicates whether firms have upgraded the ICT skills of ICT-specialized workers and/or non-ICT-specialized workers. Our analysis unfolds in two-steps. First, we perform an exploratory factor analysis on the firm-level adoption of the six technologies to identify possible patterns of conjoint adoption. This is useful both in itself, as a way to identify possible subclusters of technologies, and as a preliminary step to pave the way for the main analysis. The factor analysis yields a two-factor solution revealing two latent propensities to invest in digital and physical I4.0 technologies, respectively. Then, we run a bivariate probit model estimating the probability of ICT upskilling of ICT-specialized and/or non-ICT-specialized workers as a function of such latent propensities and a set of control variables including size, industry, location and ICT intensity. We compute the marginal effects of a percentage increase in the score on latent digital adoption and physical adoption propensities on the probability of all possible combinations of outcomes: no ICT upskilling, selective ICT upskilling of ICT workers, selective ICT upskilling of non-ICT workers, conjoint ICT upskilling. Finally, we run a multinomial logit with the same operationalizations and the same logic as a robustness check.

Our factor analysis confirms that I4.0 is a systemic phenomenon, with significant firm-level interrelations among all the six technologies considered. However, it also highlights a propensity toward purely digital technologies, namely augmented reality, big data analytics and cloud computing, and a propensity toward purely physical technologies, namely robots and 3d printing, with the internet of things taking part in both categories coherently with its hybrid digital-physical status. Our analyses show that firms adopting I4.0 technologies (of any kind) have a greater relative tendency to upskill conjointly both ICT and non-ICT workers, rather than upskilling selectively either of the two. Furthermore, both our bivariate probit and our multinomial logit analyses align with intuition in confirming that the tendency to adopt purely digital technologies has a stronger association with the ICT upskilling of any part of the workforce than the tendency to adopt purely physical technologies. However, rather interestingly, we find that also the latter tendency is positively related to ICT upskilling, especially when it is directed toward the whole workforce. These results hold, with slight variations in magnitude, across medium and large enterprises. Interestingly, small firms constitute an exception, with digital and physical adoption propensities showing no stronger association with conjoint upskilling and no difference in the strength of their association with the upskilling of any part of the workforce (ICT vs non-ICT personnel).

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on the topic. Specifically, Subsection 2.1 lays a succinct theoretical background on technological complementarities and upskilling in general, while Subsection 2.2 focuses on the recent literature on the complementarities among I4.0 technologies and their relationship with human resources. Section 3 develops our empirical analysis, presenting results (Subsection 3.2) after a thorough description of the database and methodology (Subsection 3.1). Section 4 concludes, discussing our findings in the light of extant literature and providing implications and future research directions.

2. Literature review

2.1 Technological complementarities and human resources

Technological change is one of the main engines of economic growth (Solow, 1956), but it is neither simple nor self-sufficient. Technologies often form complex systems where components are complementary (Brynjolfsson et al., 2018) and interdependent (Hughes, 1993; Rosenberg, 1979), and the architecture may matter more than its single building blocks. Such a complexity brings opportunities as well as challenges. On the one hand, the systemic nature of technology is reflected in the consolidation of concepts like combinatorial and architectural innovation, whereby mixing up technological components or subverting their overarching structure may reveal novel uses and properties (Arthur, 2009; Fleming, 2001; Henderson and Clark, 1990; Yoo et al., 2012). On the other hand, single components lagging behind in development may restrain the potential of the entire system they belong to (Bijker et al., 1987). Furthermore, functional complementarities, recombination potential and technical constraints extend beyond the level of technologies to the level of knowledge and heuristics, with know-how accumulation and learning effects playing a crucial role in the determination of adoption patterns (Martinelli, 2012). Technological interdependence may even translate into epistemological interdependence, with different technologies possibly giving rise to a new aggregate paradigm after a process of convergence (Pedota et al., 2021). These reasons, among others, underlie the frequent empirical observation of interdependencies in the adoption of technologies by firms (Battisti and Iona, 2009; Colombo and Mosconi, 1992; Wozniak, 1984).

Within systems of interdependent technologies, the human factor cannot be disregarded. Technological components do not only interact among themselves, but also with human skills. Dynamics of complementarity and substitution between technology and skills have been largely investigated both theoretically and empirically. According to the skill-biased technological change hypothesis (Autor et al., 1998; Berman et al., 1994; Bresnahan et al., 2002), automation and computerization technologies complement high-skill workers and substitute for low-skill workers. A more recent hypothesis, routine-biased technological change (Goos et al., 2009, 2014), instead suggests that such technologies complement workers performing non-routine tasks, which tend to be at the opposite ends of the spectrum of skills (high and low). While informative at high levels of aggregation, the crude education-based distinction between high and low skills can be overcome with more fine-grained taxonomies of skills, recognizing cognitive and manual dimensions (Autor and Dorn, 2013); language, reasoning, vision and movement (Elliot, 2014); creative and social intelligence (Frey and Osborne, 2017). While the skill-biased and routine-biased hypotheses diverge on the focal determinant of complementarity, they both underline the necessity to couple technological advancement with adequate human resources.

2.2. The case of I4.0

These well-established facts seem to hold to an even greater extent in the case of I4.0 technologies. According to a recent categorization by the European Patent Office (2017), it is possible to distinguish between core technologies, enabling technologies and application domains in the realm of I4.0. Core technologies are basic functional constituents like advanced sensors, processors, adaptive databases and network protocols, and their combination forms the enabling technologies traditionally associated with I4.0, such as virtual reality, 3D printing, artificial intelligence and big data analytics. However, such enabling technologies can be combined further to form new solutions into a variety of application domains, ranging from smart homes to autonomous driving and intelligent energy distribution networks. Notable examples are given by firms combining artificial intelligence with 3D printing to optimize production capacity and material selection (Valdivieso, 2020), and employing internet of things-enabled cloud-based additive manufacturing platforms to support rapid product development (Wang et al., 2019).

While there is no doubt on the dynamism and combinability of I4.0 technologies in general, more evidence is needed on which I4.0 technologies exactly complement which other and why. A related problem is understanding technical and epistemological similarities and differences within the I4.0 cluster. In an effort to evaluate whether the enabling technologies of I4.0 can be considered general purpose technologies (Bresnahan and Trajtenberg, 1995), Martinelli and colleagues (2021) provide some evidence in this direction, by estimating indicators of generality, originality and longevity for six I4.0 technologies based on patent data. They find that artificial intelligence, 3D printing, robots and the internet of things are more pervasive and original than cloud computing and big data analytics. They also find that cloud computing, big data analytics and artificial intelligence have similar industrial knowledge bases and are part of a stable pattern of joint development, diverging from 3D printing (which instead converges with robots). However, these results are not definite in highlighting technological complementarities in use at the firm level. Some micro-level evidence in this sense comes instead from a recent survey by the U.S. census bureau, finding that firms adopting advanced business technologies like robots and artificial intelligence very often also implement cloud services and widespread digitization (Zolas et al., 2021). While most mechanisms of firm-level complementarity in adoption are theoretically clear, notably data-gathering technologies (e.g. the internet of things) fueling data-hungry technologies (e.g. artificial intelligence and big data analytics), their relevance in practice is still uncertain, calling for more empirical investigations at all levels of analysis.

Besides technological complementarities, the human factor is of paramount importance in the I4.0 context as well (Lorenz et al., 2015). At the level of the labor market, views are rather mixed (Ciarli et al., 2021): some are more pessimistic, forecasting the elimination of some jobs as a consequence of I4.0 (Acemoglu and Restrepo, 2019; Frey and Osborne, 2017; Korinek and Stiglitz, 2017); others are more optimistic, predicting the emergence of new jobs and the improvement of extant ones (Arntz et al., 2017; Autor and Salomons, 2018; Felten et al., 2019); still others take a neutral perspective (Das et al., 2020; Nedelkoska and Quintini, 2018). Conversely, at the level of skills there is a strong consensus emphasizing the need to bridge the skill gap and prepare the workforce for I4.0 (Galaske et al., 2017; Motyl et al., 2017; Ras et al., 2017; Schallock et al., 2018). However, research on the interaction between I4.0 technologies and human resources is still relatively scarce (Neumann et al., 2020). Given their digital constituents and their data-driven nature, I4.0 technologies need to be complemented by STEM skills like statistical knowledge, programming, coding, and the ability to cope with large amounts of data and innovative interfaces. In this respect, Pinzone and colleagues (2020) provide a comprehensive overview of the technical skills required by I4.0 in the subfields of operations management, supply chain management, product-service information management, data science management and IT-OT integration management. Other works convey a more boundary-spanning perspective, pointing to the necessity for cross-functional roles, broader skillsets and lifelong learning (Fisk, 2017; Onar et al., 2018). Furthermore, an increasing body of research is underlining the relevance of soft skills in the I4.0 era, including emotional intelligence, critical thinking, communication, leadership, and creativity (Ciarli et al., 2021; Deming, 2017; Maisiri et al., 2019; Pedota and Piscitello, 2020).

While this picture suggests the necessity by firms to endow themselves with adequate bundles of I4.0 technologies and human skills to remain competitive, much is still to be learnt on the characterization of such bundles. For example, while it would be tempting to lean toward a selective upskilling of the workforce based on the precise technical requirements of I4.0, the boundary-spanning nature and soft skill orientation of I4.0 point to the necessity of a more holistic upskilling (Hecklau et al., 2016).

Firms are social context permeated by continuous multilevel interactions, facilitated and magnified by the massive machine-to-machine, human-to-machine and human-to-human interconnectivity provided by advanced technologies. Thus, upskilling isolated portions of the workforce (notably ICT employees) may no more be sufficient in the I4.0 context. A concurrent upskilling of ICT and non-ICT employees may be necessary, constituting the embodiment of the systemic character of I4.0 technologies at the level of human resources.

With the present work, we perform a comprehensive empirical investigation taking into account both the technological and the human side of I4.0, which are usually considered separately. We aim to ascertain first the extent to which augmented reality, big data analytics, cloud computing, the internet of things, robots and 3D printing are correlated among themselves at the firm level. Most importantly, we do not only look at pairwise correlations, but we aim to capture patterns of conjoint adoption of multiple technologies, thus contributing to the literature on I4.0 technological complementarities. Then, we build on the previous step to understand which patterns are most strongly associated with the ICT upskilling of which parts of the workforce (a selective ICT upskilling of ICT workers, a selective ICT upskilling of non-ICT workers, or the ICT upskilling of the whole workforce), thus contributing to the literature on the interaction between I4.0 and human skills. In both steps, we replicate the analysis on subsamples according to firm size, in order to test for possible differences in I4.0 technologies adoption and upskilling patterns across small, medium and large enterprises.

3. Empirical analysis

3.1 Description of the sample and methodology

The database[1] underlying our empirical investigation comes from a cross-sectional survey on information and communication technologies (ICT) developed in 2018 conjointly by Eurostat and ISTAT, the Italian institute of statistics, in collaboration with the European commission. The survey

[1] Information on the database and the sampling procedure comes from the methodological note provided by ISTAT.

aims at providing a variegated ensemble of data about the implementation of ICT technologies in Italian firms with at least 10 employees. Such data include the presence and training of ICT workers, the use of e-commerce and social media, the use of electronic invoicing, the strategic determinants of the digital transformation, and, most notably, the presence of investments in augmented reality, big data analytics, cloud computing, the internet of things, robots and 3D printing, both in 2016 and 2017. The reference population for the survey consists of italian firms with at least 10 employees operating in any of the following sectors, according to the Italian ATECO classification: manufacturing (C); supply of electricity, gas, steam and air conditioning (D); water supply, sewerage and waste management (E); construction (F); wholesale and retail trade and repair of motor vehicles and motorcycles (G); transport and storage (H); accommodation and catering services (I); information and communication services (J); real estate activities (L); professional, scientific and technical activities (M, except division 75); rental, travel agencies and business support services (N); repair of computers and communications equipment (group 95.1 of section S).

The whole sub-population of firms with at least 250 employees is included in the database, whereas firms with a number of employees between 10 and 249 have been sampled. The sampling method follows a stratified random logic whereby each observation belonging to a given stratum has the same probability of being selected. Strata are defined according to industry (at a predefined level of aggregation), number of employees (10-49, 50-99, 100-249, >= 250) and geographical location. The total dimension of the sample is 21,934 firms. As a first step, we divided the sample into three categories based on firm size, distinguishing between 13,761 small firms, 4,716 medium firms and 3,457 large firms. To this end, we relied on the revenue criterion, using as reference boundaries those indicated by the European commission to recognize small and medium enterprises[2]. Subsequently, we identified the following variables of interest:

[2] Referring to the EU recommendation 2003/361, we identified firms with revenues lower than or equal to 10 million as small firms, firms with revenues between 10 and 50 million as medium-sized firms, and the remaining firms as large ones. While we are aware that revenues alone constitute an imperfect proxy for size, we believe it does not lead to significant biases for the purposes of the present study.

- A binary variable taking the value of 1 if the firm engaged in the ICT upskilling of ICT workers in 2017, and 0 otherwise.
- A binary variable taking the value of 1 if the firm engaged in the ICT upskilling of non-ICT workers in 2017, and 0 otherwise.
- A vector of six binary variables, each of which takes the value of 1 if the firm invested in the corresponding I4.0 technology in both years 2016 and 2017[3], the six technologies being augmented reality, big data analytics, cloud computing, the internet of things, advanced robots and 3D printing.

The following tables provide a description of the sample with respect to these focal dimensions.

INSERT TABLE I ABOUT HERE

INSERT TABLE II ABOUT HERE

INSERT TABLE III ABOUT HERE

Not surprisingly, firm size seems to play a definite role in the frequency of adoption of I4.0 technologies (see Table I). While most large firms and about one third of medium firms adopted at least one technology, the overwhelming majority of small firms did not adopt any of the six technologies in the dataset (12,061 out of 13,661 firms). Conversely, there is a high degree of uniformity in the patterns of adoption by adopting firms (see Table II). The most frequently adopted technology is cloud computing, constituting 60%, 49% and 41% of the total instances of adoption in small, medium and large firms, respectively. The internet of things follows, constituting 23% of total instances of adoption across all firm size categories. Big data analytics scores 10%, 13% and 16% in small, medium and large firms respectively, whereas augmented reality and 3D printing show a relatively low rate of adoption across all size categories (2% to 4%). Advanced robots are the only

[3] We opted to consider investment in both years 2016 and 2017 as a proxy for adoption of each of the six I4.0 technologies in order to capture a more solid commitment to the technology. Given that the database lacks the extent of the investments, considering only 2017 or only 2016 would have entailed the risk of defining as adopters firms with minimal investments.

case where a significantly different pattern can be observed across size categories, as they constitute only 2% of total instances of adoption in small firms, as opposed to 9% and 13% in medium and large firms respectively. This may be due to medium and large firms being more skewed toward large-scale manufacturing and construction segments, where robots are more frequently used. It is also worth noting that, while cloud computing is the most frequently adopted technology across all size categories, it has a much higher relative frequency of adoption in small firms. This may be due to the technical characterization of cloud computing, which allows adopting firms to tap into external storage and computing capacity, a feature that is most valuable for small firms due to their relatively limited resources.

As for the ICT upskilling patterns, Table I provides valuable descriptive insights. There are relevant differences both between upskilling patterns of adopters vs non-adopters, and across firm size categories within adopters and non-adopters. Small firms tend to upskill the least, with 85% of non-adopters and 56% of adopters performing no ICT upskilling. Conversely, large firms upskill the most, especially the whole workforce as opposed to a part of it (27% of non-adopters and 49% of adopters upskill conjointly). Medium firms lie in between, and they seem to show a relatively higher propensity toward selective non-ICT upskilling. Interestingly, there is a significantly lower proportion of non-upskilling firms in the adopters category, across all firms sizes (56%, 47% and 25% as opposed to 85%, 70% and 47% in small, medium and large firms, respectively). The other tendency that varies significantly and uniformly between adopters and non-adopters is conjoint upskilling, with adopters performing it much more frequently than non-adopters, across all firm size categories (18%, 25% and 49% as opposed to 3%, 10% and 27% in small, medium and large firms, respectively). On the contrary, patterns of selective upskilling are less uniform. Small adopting firms tend to selectively upskill ICT workers much more frequently (12% as opposed to 3%), and non-ICT workers slightly more frequently (12% as opposed to 9%), with respect to non-adopters of the same size. Medium adopting firms have a slightly higher selective upskilling frequency relative to non-adopters in both the ICT and the non-ICT case. Large adopting firms have a slightly higher selective ICT upskilling frequency and, most interestingly, a lower selective non-ICT upskilling frequency with respect to non-adopters of the same size. This may suggest that the great tendency toward conjoint upskilling by large adopting firms eats away the propensity to upskill selectively non-ICT employees.

These insights are corroborated by the tetrachoric correlation matrix (Table III). Both the ICT upskilling of ICT workers and the ICT upskilling of non-ICT workers have a definite negative correlation with the small size category and a definite positive correlation with the large size category, while being neutral with respect to the medium size category. Furthermore, each of the six technologies has at least a moderate positive correlation with both kinds of upskilling, with coefficients ranging from 0.34 to 0.51. This complements from a different angle the indication given by Table I: adopting firms have a stronger tendency toward ICT upskilling, and this holds for each of the six I4.0 technologies considered. A further insight emerging specifically from the tetrachoric correlation matrix (Table III) concerns the interdependencies in technology adoption by firms. All the six technologies are indeed interrelated at least moderately, with pairwise correlation coefficients ranging from 0.32 to 0.64. However, a subtlety that can already be appreciated from the matrix concerns the different magnitudes of the correlation. For example, big data analytics has a much stronger correlation with cloud computing and augmented reality (0.64 and 0.61, respectively), rather than advanced robots and 3D printing (0.31 and 0.41, respectively). The latter two are instead strongly correlated among themselves (0.64). This evidence seems to resonate with the realization that big data and cloud computing have similar industrial knowledge bases, which diverge from robots and 3D printing (Martinelli et al., 2021). Overall, the correlation matrix indicates that patterns of conjoint adoption may be present. However, pairwise correlation coefficients on their own are not enough to spot them.

To this end, we conducted a factor analysis based on the correlation matrix among the six technologies in the dataset (leaving all the other variables aside). The Bartlett test of sphericity is significant at less than 1% and the Kaiser-Meyer-Olkin measure of sampling adequacy is 0.76, indicating the suitability of a factor analysis. We extracted two factors and applied the Varimax rotation technique to facilitate interpretation, identifying a latent propensity toward digital I4.0 technologies (i.e. augmented reality, big data analytics and cloud computing) and a latent propensity toward physical I4.0 technologies (i.e. robots and 3D printing) (more details on the interpretation of factor loadings in the next Subsection). Then, we replicated the whole process on each subsample based on firm size (small, medium and large firms), identifying the same two propensities in all cases, with little variation in factor loadings. Factor loadings of the whole sample as well as each subsample are reported in Table IV.

INSERT TABLE IV ABOUT HERE

Subsequently, we calculated the scores on the two extracted factors for each observation and used them as the focal independent variables in a bivariate probit regression[4] concurrently estimating the probability of upskilling ICT and non-ICT employees as a function of a set of regressors. Besides the two factor scores (i.e. digital and physical adoption propensities), we included the following controls as independent variables, at the highest level of detail provided by the database:

- The revenue class. Besides segmenting the sample in three subsamples based on revenues, we used classes of revenues at a finer level of granularity as control variables within each subsample. While we believe three classes of size are enough to analyze differences in the behavior of each variable of interest as size varies, a higher level of granularity is necessary to better control for the confounding effect of size.
- The geographic location. We used 4 binary variables to capture the location of the firm within Italy: northeast, northwest, center, south and islands. Location plays indeed an important role due to the stronger presence of key industrial clusters in the north of Italy as opposed to the

[4] We multiplied the factor score by 100 to facilitate interpretation of the marginal effects, without affecting statistical significance.

south and the islands. This may confound the relationship between upskilling and technology adoption propensity.

- The share of ICT workers employed by the firm. We used the percentage of ICT workers as a proxy for the degree of importance that ICT activities have within the firm. This is the most important confounder to control for, as it greatly affects both the probability of ICT upskilling and the propensity toward digital I4.0 technologies.
- The industry. We used a vector of 11 binary variables to account for the sector each firm belongs to, according to the first level of aggregation of the ATECO classification: manufacturing (C); supply of electricity, gas, steam and air conditioning (D); water supply, sewerage and waste management (E); construction (F); wholesale and retail trade and repair of motor vehicles and motorcycles (G); transport and storage (H); accommodation and catering services (I); information and communication services (J); real estate activities (L); professional, scientific and technical activities (M, except division 75); rental, travel agencies and business support services (N); repair of computers and communications equipment (group 95.1 of section S). Given the presence of the share of ICT workers as a very effective control for ICT intensity, we regard this level of aggregation as satisfactory.

We performed four different bivariate probit regression with the ICT upskilling of ICT workers and the ICT upskilling of non-ICT workers as the two dependent variables. One was performed on the whole sample, while the remaining three were performed on each subsample based on firm size. The four regressions do not differ in any aspect except for the factor scores, which are calculated separately according to the four different factor analyses based on the specific correlation matrix of each subsample[5]. After running each biprobit model, we computed the marginal effects of a percentage increase in the factor scores capturing the digital and physical adoption propensities on each possible combination of outcomes: no ICT upskilling, selective ICT upskilling of ICT workers,

[5] However, even using the same factor scores would not have produced significantly different results, as the factor loadings are similar across the four separate factor analyses (see Table IV).

selective ICT upskilling of non-ICT workers, and conjoint ICT upskilling. Finally, we run a multinomial logit model adopting the three aforementioned combinations of ICT upskilling as the dependent variables (i.e. selective ICT upskilling of ICT workers, selective ICT upskilling of non-ICT workers, and conjoint ICT upskilling) and the absence of upskilling as the baseline, keeping the same controls and focal independent variables (i.e. the two latent propensities).

3.2. Results

A first relevant result emerges from the factor analysis. As Table IV shows, augmented reality, big data analytics and cloud computing load heavily on the first factor, whereas 3D printing and robots load heavily on the second one. The remaining technology, the internet of things, has an average loading on both factors. This outcome offers a clear interpretation: the first and the second factor represent latent propensities to adopt digital and physical I4.0 technologies, respectively. Augmented reality, big data analytics and cloud computing are all characterized by a digital nature and high degree of immateriality: they are concerned with data elaboration and visualization, rather than object creation and manipulation. The exact opposite holds for 3D printing and robots, which are primarily used for manufacturing and moving physical objects. This interpretation is also coherent with the indetermined status of the remaining technology, the internet of things. Referring to the equipment of objects with intelligent sensors creating a bridge between the physical and the digital world, the internet of things is well-suited to represent a digital-physical hybrid having a comparable loading on both factors.

Another aspect worth underlining is the absence of low or negative loadings on either factor. This suggests that the existence of two well-defined propensities does not induce a polarization in adoption. In other terms, the propensity to adopt digital (physical) technologies does not limit the adoption of physical (digital) technologies. On the contrary, it can be argued that each propensity implies the other, though to a significantly lower extent. This reflects the positive bivariate correlations among all technologies (Table III), and it is coherent with the view of I4.0 as a systemic phenomenon, characterized by multidirectional complementarities (EPO, 2017). Such complementarities seem to be correctly pursued by firms through conjoint adoption, and some technologies tend to be adopted conjointly with a higher relative frequency, according to the two patterns we identified (i.e. digital and physical adoption propensities).

The associations between the two identified propensities and ICT upskilling are reported in the following tables. Table V reports the marginal effects of a percentage increase in each factor's score on the probability of each outcome resulting from the bivariate probit estimations; Table VI reports the Wald tests for the difference in the coefficients of the two factors in the bivariate probit estimations; Table VII reports the multinomial logit coefficient of each factor score. All results refer to the whole sample as well as each subsample based on firm size.

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INSERT TABLE VII ABOUT HERE

First, both propensities have a negative, sizable and statistically significant relationship with the absence of upskilling (see Table V). This is true for all firm size categories. An increase of 10% in digital adoption propensity reduces by 2.7%, 3.7% and 4.1% the probability of no ICT upskilling in small, medium and large firms, respectively. An increase of 10% in physical adoption propensity reduces by 2.8%, 1.5% and 2.3% the probability of no ICT upskilling in small, medium and large firms, respectively. Delving into the specificities of the three combinations of upskilling, it is worth comparing the marginal effects of both propensities on the probability of conjoint upskilling as opposed to selective upskilling (see Table V). The propensity to adopt I4.0 technologies, whether physical or digital, correlates more strongly with conjoint upskilling rather than selective upskilling, at least in medium and large firms. A 10% increase in digital adoption propensity augments by 2.1% and 4.1% the probability of conjoint upskilling in medium and large firms respectively, while it only augments by 0.8% the probability of both kinds of selective upskilling in medium firms, and it has a close to zero and statistically insignificant effect on selective upskilling in large firms. A 10% increase in physical adoption propensity augments by 0.8% and 2.3% the probability of conjoint upskilling in medium and large firms respectively, while it has a statistically insignificant effect on both kinds of selective upskilling both in medium and large firms. Small firms constitute an exception, with the marginal effects of both propensities being highest on non-ICT upskilling rather than conjoint upskilling (1.3% vs 0.8% and 1.6% vs 0.7%, in front of a 10% increase in digital adoption and physical adoption propensities respectively, as Table V shows). This may be due to the higher specialization and more limited resources of small firms, which makes conjoint upskilling a priori less likely (as also reflected in Table I) and the upskilling of non-ICT workers more urgent (more details on this conjecture in the concluding section).

Taken together, these pieces of evidence imply that adoption of I4.0 technologies goes in tandem with ICT upskilling. Depending on industrial specificities, resource availability and firm-level idiosyncrasies, upskilling may be directed toward either the whole workforce or a part of it, but it is in any case likelier than its absence, as confirmed indirectly by the bivariate probit estimations and directly by the multinomial logit coefficients, which employ "no upskilling" as the baseline (see Table VII). However, the likelihood of conjoint upskilling for medium and large adopting firms is even higher, suggesting that I4.0 and human skills form indeed a complex sociotechnical system, where technological adoption (whether digitally or physically oriented) should be ideally complemented by a holistic upskilling of the workforce.

Unsurprisingly, there is a difference in the magnitude and, in some cases, even the statistical significance of the digital adoption propensity marginal effects as opposed to the physical adoption propensity ones (Table V). Digital adoption propensity almost always has a higher marginal effect on the probability of all kinds of upskilling (for both ICT-specialized and non-ICT specialized personnel)[6], the only exception being selective upskilling of non-ICT employees in small firms[7]. In the case of medium and large firms, the physical adoption propensity marginal effects on selective upskilling are not even statistically significant, besides being lower than their digital counterparts. A series of Wald tests for the difference in factor coefficients confirm that digital and physical adoption propensities are differently associated with the probability of ICT upskilling in all cases, except for small firms (see Table VI). The multinomial logit estimations corroborate these results, showing a higher coefficient for digital adoption propensity in all cases, except for small firms (see Table VII).

The stronger association between digital adoption propensity and ICT upskilling is not surprising, as digital technologies are by definition closer to the domain of ICT. However, intuition would suggest that, precisely for this reason, the consequent ICT upskilling would be directed mainly toward ICT employees, who are supposed to be the direct operators of digital technologies. Intuition would also suggest that, being farther from the ICT domain, physical technologies have no significant relationship with ICT upskilling, whether it be directed toward ICT or non-ICT employees. Instead, our results seem to suggest that both physical and digital I4.0 technologies require ICT skills and, most importantly, they require a holistic upskilling on the part of both ICT-specialized and non-ICT specialized personnel. In particular, physical adoption propensity relates positively and significantly only to the conjoint ICT upskilling of both ICT and non-ICT employees, and not to the selective ICT upskilling of either of the two. Not only does this imply that even physical I4.0 technologies require ICT skills, but it also implies that, taken together, they definitely require those skills on the part of both ICT and non-ICT employees. Overall these results suggest that both digital and physical I4.0 technologies form a new language that requires ICT skills to be interpreted and transmitted. Besides strengthening the ICT skills of ICT employees, this language also requires endowing non-ICT

[6] Please note that, in the case of "no upskilling", the marginal effect of the digital adoption propensity is lower. However, being a negative marginal effect on the negative of upskilling, the direction is the same as in the other cases, from a conceptual viewpoint.

[7] Strictly speaking, the magnitude is (slightly) lower also in the case of selective ICT upskilling by large firms. However, it should not be considered, as the physical adoption propensity coefficient is not statistically significant in that case.

employees with ICT skills, in order to make sense of the new organizational reality together with their ICT-specialized colleagues.

4. Discussion and conclusion

Technological complementarities and upskilling constitute wide and intertwined research areas. Technologies form complex systems (Hughes, 1993; Rosenberg, 1979), and their interdependent characteristics determine patterns of coevolution over time (Martinelli et al., 2021), possibly culminating in the formation of aggregate technological paradigms after a process of convergence (Pedota et al., 2021). At the firm level, these aspects, among others, make it optimal to adopt some technologies in conjunction with others, a frequently observed empirical occurrence (Battisti and Iona, 2009; Colombo and Mosconi, 1992; Wozniak, 1984). Furthermore, interdependence goes beyond the technological realm and extends to human resources. To reveal their full potential, technologies need to be complemented by appropriate human skills. The skill-biased (Autor et al., 1998; Berman et al., 1994; Bresnahan et al., 2002), and, subsequently, routine-biased (Goos et al., 2009, 2014) technological change hypotheses have characterized a long-lasting debate about different types of human skills complementing or substituting for automation and computerization technologies, a debate that is still alive, also due to the dynamic nature of technological change.

Nowadays, many find a discontinuity in the ongoing process of technological change, to the point of identifying a fourth industrial revolution, disrupting competition dynamics and giving rise to the innovative business models and smart factories that underlie the so-called I4.0 (Kagermann, 2015; OECD, 2017; Osterrieder et al., 2020; Sung, 2018). Some works try to analyze the generally established concepts of technological complementarity and interdependence within the context of I4.0, ascertaining that some technologies have more compatible knowledge bases than others (e.g. artificial intelligence, cloud computing and big data analytics) (Martinelli, 2021), and that firms tend to show patterns of hierarchical adoption, with advanced I4.0 business technologies often presupposing widespread digitization (Zolas et al., 2021). Other works instead focus on the human side of the matter, adopting labor market perspectives (e.g. Acemoglu and Restrepo, 2019; Autor and Salomons, 2018; Das et al., 2020), skill-centric views (Galaske et al., 2017; Motyl et al., 2017; Ras et al., 2017; Schallock et al., 2018) or panoramic outlooks on the human factor (e.g. Neumann, 2020). However, research on both the technological and the human side is still scant, and, above all, the two sides are usually considered separately in extant theoretical and empirical investigations.

In the present work, we provide a first attempt to investigate the technological and human sides of I4.0 conjointly, leveraging a large cross-sectional database of Italian firms to highlight a series of important findings. First, while confirming that I4.0 is a systemic phenomenon (EPO, 2017), we also identify two distinct latent propensities to invest primarily (though not exclusively) in either digital or physical I4.0 technologies at the firm level. Since a considerable part of the impulse toward technological development comes from R&D, this may have implications both at the level of the firm and at the level of technological change. Regarding the former, the present work indicates that firms may want to channel their resources (Barney, 1991), routines (Nelson and Winter, 1982) and absorptive capacity (Cohen and Levinthal, 1990) toward the exploitation of precise subclusters of I4.0 technologies, depending on their needs. For instance, managers of digitally oriented firms may want to hire employees well-versed not only in big data analytics, but also in cloud computing and augmented reality, and encourage the development of heuristics supporting the use and recombination of these particular technologies. These and many other strategic implications are likely to stem from the identification of subclusters of technologies that are complementary in use. Regarding general dynamics of technological change, our results resonate with the work of Martinelli and colleagues (2021), giving an indication on the fact that big data analytics, cloud computing and augmented reality, as well as robots and 3D printing, may eventually become part of two unique, aggregate technological paradigms (Pedota et al., 2021). However, overall evidence is still insufficient and technological trajectories are currently too unpredictable to draw definite conclusions in this regard.

The present work also sheds new light on the intertwinement between I4.0 technologies and skills. First, it provides evidence that the adoption of I4.0 technologies, whether digital or physical, is likelier to be coupled with a conjoint ICT upskilling of both ICT and non-ICT employees, rather than a selective upskilling of either of the two. Second, it suggests that even the propensity to adopt physical I4.0 technologies like robots and 3D printing is directly and positively related to the conjoint ICT upskilling of ICT and non-ICT specialized personnel (although with a weaker magnitude that the propensity to adopt digital I4.0 technologies). Beyond their inherent degree of digitalization, all I4.0 technologies seem to constitute the foundation of a new language that all employees (both ICT and non-ICT) need to get familiar with, through the acquisition of appropriate ICT skills. This interpretation also resonates with the importance of sociability and creativity in the I4.0 domain (Ciarli et al., 2021; Pedota and Piscitello, 2020), which favor employee interconnection and technological recombination.

A second implication descending from the findings above concerns the labor market. The tendency for conjoint upskilling seems to indicate that there is no clear-cut separation between the ICT skills needed by ICT employees and non-ICT employees. While ICT employees are inherently drawn toward the corpus of skills needed for I4.0, non-ICT employees may be tempted to believe that they can disregard the digital side of technology. In the light of our findings, familiarity with digital I4.0 technologies and innovative interfaces (e.g. augmented reality) may constitute an increasingly important competitive advantage in the labor market, having the two-fold effect of making workers possessing it more appealing ex-ante, and facilitating ex-post the process of upskilling enacted by medium and large firms, thanks to the self-sustaining properties of learning and knowledge cumulation.

As a future research direction, we recommend developing additional empirical and theoretical insights into the reasons why small firms constitute an exception to our findings. Unlike the other cases, in small firms digital adoption propensity does not relate more strongly to ICT upskilling than physical adoption propensity. Furthermore, selective non-ICT upskilling is the outcome most strongly associated with either propensity, rather than conjoint upskilling. We conjecture that this may be due to a combination of resource constraints and higher specialization. The former limits the ability of small firms to engage in conjoint upskilling, while the latter implies a lower indirect exposure of non-ICT employees to digital technologies. Taken together, these facts make it necessary to selectively upgrade the ICT skills of non-ICT employees, to help them take part in the new I4.0-driven interconnected organizational reality together with their ICT colleagues. However, it is impossible to draw conclusions in this regard without ad hoc qualitative insights. If the hypothesis on resource constraints were true, it would have important policy implications, as small firms would need to be subsidized not only for the adoption of I4.0 technologies, but also for the appropriate upskilling of their workforce. More generally, we encourage further empirical and theoretical efforts aimed at making sense of the intertwinement between technological and skill complementarities in the context of I4.0. As the fourth industrial revolution unfolds, sociotechnical interactions are likely to become even more important than each component on its own.

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Table I. Type of upskilling by firm size and adoption

Status	*Type of upskilling*	*Small*	*Medium*	*Large*	*Total*
Adopter	*No upskilling*	901 *(50%)* *(56%)*	542 *(30%)* *(47%)*	371 *(20%)* *(25%)*	1814 *(100%)* *(43%)*
	Only ICT upskilling	208 *(38%)* *(13%)*	124 *(23%)* *(11%)*	215 *(39%)* *(15%)*	547 *(100%)* *(13%)*
	Only NON-ICT upskilling	198 *(35%)* *(12%)*	192 *(34%)* *(17%)*	174 *(31%)* *(12%)*	564 *(100%)* *(13%)*
	Conjoint upskilling	293 *(23%)* *(18%)*	288 *(22%)* *(25%)*	717 *(55%)* *(49%)*	1298 *(100%)* *(31%)*
	Total	1600 *(38%)* *(100%)*	1146 *(27%)* *(100%)*	1477 *(35%)* *(100%)*	4223 *(100%)* *(100%)*
Non-adopter	*No upskilling*	10338 *(75%)* *(85%)*	2505 *(18%)* *(70%)*	926 *(7%)* *(47%)*	13769 *(100%)* *(78%)*
	Only ICT upskilling	383 *(47%)* *(3%)*	209 *(26%)* *(6%)*	221 *(27%)* *(11%)*	813 *(100%)* *(5%)*
	Only NON-ICT upskilling	1079 *(58%)* *(9%)*	490 *(26%)* *(14%)*	291 *(16%)* *(15%)*	1860 *(100%)* *(11%)*
	Conjoint upskilling	361 *(28%)* *(3%)*	366 *(29%)* *(10%)*	542 *(43%)* *(27%)*	1269 *(100%)* *(7%)*
	Total	12161 *(69%)* *(100%)*	3570 *(20%)* *(100%)*	1980 *(11%)* *(100%)*	17711 *(100%)* *(100%)*

The Table shows the number of firms that do not upskill, upskill selectively ICT employees, upskill selectively non-ICT employees and upskill conjointly, categorizing them according to their size and their status in terms of technological adoption. The status of adopter means that the firm has adopted at least one of the six technologies in the dataset, while the status of non-adopter means that the firm has adopted none of the six technologies in the dataset. Percentages to the side of absolute numbers indicate the relative frequency with respect to the horizontal dimension (i.e. type of upskilling), whereas percentages below indicate the relative frequency with respect to the vertical dimension (i.e. firm size). Percentages are rounded to the nearest integer.

Table II. Technologies adopted by firm size

Technology	*Small*	*Medium*	*Large*	*Total*
Augmented reality	52 *(32%)* *(3%)*	38 *(23%)* *(2%)*	73 *(45%)* *(3%)*	163 *(100%)* *(3%)*
Big data analytics	201 *(26%)* *(10%)*	194 *(25%)* *(13%)*	388 *(50%)* *(16%)*	783 *(100%)* *(13%)*
Cloud computing	1200 *(40%)* *(60%)*	765 *(26%)* *(49%)*	1003 *(34%)* *(41%)*	2968 *(100%)* *(50%)*
Internet of things	461 *(33%)* *(23%)*	362 *(26%)* *(23%)*	558 *(40%)* *(23%)*	1381 *(100%)* *(23%)*
3D printing	34 *(18%)* *(2%)*	49 *(26%)* *(3%)*	103 *(55%)* *(4%)*	186 *(100%)* *(3%)*
Advanced robots	45 *(9%)* *(2%)*	139 *(28%)* *(9%)*	318 *(63%)* *(13%)*	502 *(100%)* *(8%)*
Total	1993 *(33%)* *(100%)*	1547 *(26%)* *(100%)*	2443 *(41%)* *(100%)*	5983 *(100%)* *(100%)*

The Table shows the number of firms that adopt each of the six I4.0 technologies in the dataset, categorizing them according to their size. Percentages to the side of absolute numbers indicate the relative frequency with respect to the horizontal dimension (i.e. the technology), whereas percentages below indicate the relative frequency with respect to the vertical dimension (i.e. firm size). Percentages are rounded to the nearest integer.

Table III. Tetrachoric correlation matrix among focal variables

Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*
(1) ICT upskilling	1.00										
(2) NON-ICT upskilling	0.72	1.00									
(3) Firm size: small	-0.51	-0.45	1.00								
(4) Firm size: medium	0.08	0.13	-1.00	1.00							
(5) Firm size: large	0.59	0.49	-1.00	-1.00	1.00						
(6) Big data analytics	0.51	0.43	-0.42	0.05	0.45	1.00					
(7) Augmented reality	0.46	0.36	-0.28	0.02	0.32	0.61	1.00				
(8) Cloud computing	0.52	0.39	-0.35	0.09	0.38	0.64	0.48	1.00			
(9) Internet of things	0.44	0.35	-0.37	0.08	0.40	0.55	0.49	0.50	1.00		
(10) 3D printing	0.44	0.36	-0.42	0.06	0.41	0.41	0.53	0.41	0.48	1.00	
(11) Advanced robots	0.39	0.34	-0.60	0.08	0.55	0.37	0.36	0.32	0.51	0.64	1.00

The Table shows the tetrachoric correlation coefficients for every couple of focal variables. Variables are arbitrarily listed from 1 to 11. The leftmost column reports the full name of the variable besides its reference number, whereas the uppermost row reports only the reference number, for graphical convenience.

Table IV. Factor loadings by firm size

Factor	*Technology*	*Small*	*Medium*	*Large*	*Whole sample*
Digital adoption propensity	*Augmented reality*	0.6271	0.6321	0.5589	0.6080
	Big data analytics	0.7603	0.6902	0.7861	0.7591
	Cloud computing	0.7745	0.5862	0.6456	0.6768
	Internet of things	0.5054	0.5184	0.4912	0.5269
	3D printing	0.2289	0.2420	0.2974	0.3274
	Advanced robots	0.1116	0.1782	0.1226	0.2340
Physical adoption propensity	*Augmented reality*	0.3381	0.2814	0.3956	0.3740
	Big data analytics	0.1892	0.1358	0.1979	0.2696
	Cloud computing	0.1086	0.2541	0.1602	0.2491
	Internet of things	0.4893	0.4361	0.4072	0.4774
	3D printing	0.7191	0.6455	0.6847	0.7033
	Advanced robots	0.6591	0.6021	0.7112	0.7012

The Table summarizes the output of the factor analyses on the whole sample and on each subsample based on firm size. Each column from “small” to “whole sample” constitutes the output of a separate factor analysis based on the polychoric correlation matrix of the corresponding subsample, and reports the rotated factor loadings for each technology on the factor indicated in the leftmost column (digital adoption propensity and physical adoption propensity).

Table V. Bivariate probit marginal effect coefficients by firm size

Firm size category	Outcome	Digital propensity marginal effect	Physical propensity marginal effect
	No upskilling	-0.0036***	-0.0024***
Whole sample	Only ICT upskilling	0.0008***	0.0005***
	Only NON-ICT upskilling	0.0012***	0.0002***
	Conjoint upskilling	0.0016***	0.001***
	No upskilling	-0.0027***	-0.0028***
	Only ICT upskilling	0.0006***	0.0005***
Small	Only NON-ICT upskilling	0.0013***	0.0016***
	Conjoint upskilling	0.0008***	0.0007***
	No upskilling	-0.0037***	-0.0015**
	Only ICT upskilling	0.0008***	0.0002
Medium	Only NON-ICT upskilling	0.0008**	0.0005
	Conjoint upskilling	0.0021***	0.0008**
	No upskilling	-0.0041***	-0.0023***
	Only ICT upskilling	0.0004*	0.0005
Large	Only NON-ICT upskilling	-0.0004	-0.0005
	Conjoint upskilling	0.0041***	0.0023***

Industry controls: included
Size controls: included
Geographical controls: included
ICT intensity controls: included

The Table summarizes the output of the bivariate probit analyses on the whole sample and on each subsample based on firm size . It reports the marginal effect of a percentage increase in each of the two factor scores indicated in the last two columns on ev ery possible outcome in terms of upskilling, for the whole sample as well as each subsample based on firm size (as indicated by the leftmost column). Three stars indicate a p-value of 1% or lower; two stars indicate a p-value between 1% and 5%; one star indicates a p-value between 5% and 10%. The absence of stars indicates that the coefficient is not statistically significant.

Table VI. Wald tests for the difference in factor coefficients

Outcome	*Small*	*Medium*	*Large*	*Whole dataset*
ICT upskilling	0.4304	0.0061	0.0142	0.0001
Non-ICT upskilling	0.6105	0.0759	0.0053	0.0029

The Table reports the level of significance of a series of Wald tests following the bivariate probit estimations on the whole sample as well as each subsample based on firm size. The null hypothesis is "the difference between the coefficients for digital adoption propensity and physical adoption propensity is zero", with coefficients referring to the dependent variable indicated in the leftmost column. Levels of significance suggest that the null hypothesis can be safely rejected for the whole database as well as large firms with respect to both ICT and non-ICT upskilling. It can also be rejected in the case of medium firms, although with a weaker level of significance with respect to non-ICT upskilling. It can definitely not be rejected in the case of small firms.

Table VII. Multinomial logit coefficients by firm size

Firm size category	Outcome	Digital propensity multinomial logit coefficient	Physical propensity multinomial logit coefficient
			-
	No upskilling	baseline	baseline
Whole sample	Only ICT upskilling	0.0195***	0.0132***
	Only NON-ICT upskilling	0.0119***	0.0079***
	Conjoint upskilling	0.028***	0.0175***
	No upskilling	baseline	baseline
	Only ICT upskilling	0.023***	0.027***
Small	Only NON-ICT upskilling	0.0136***	0.0222***
	Conjoint upskilling	0.0327***	0.0292***
	No upskilling	baseline	baseline
	Only ICT upskilling	0.0181***	0.0072
Medium	Only NON-ICT upskilling	0.0111***	0.006
	Conjoint upskilling	0.0235***	0.009**
	No upskilling	baseline	baseline
	Only ICT upskilling	0.0129***	0.0033
Large	Only NON-ICT upskilling	0.0074***	-0.004
	Conjoint upskilling	0.0234***	0.0123***

Industry controls: included
Size controls: included
Geographical controls: included
ICT intensity controls: included

The Table summarizes the output of the multinomial logit analyses on the whole sample and on each subsample based on firm size. For each subsample indicated in the leftmost column, it reports the multinomial logit coefficients for the two factors on each combination of upskilling, adopting "no upskilling" as the baseline. Three stars indicate a p-value of 1% or lower; two stars indicate a p-value between 1% and 5%; one star indicates a p-value between 5% and 10%. The absence of stars indicates that the coefficient is not statistically significant.