



Digital adoption during COVID-19 : Cross-country evidence from microdata

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Introduction

- The COVID-19 pandemic had several implications for economic outcomes, e.g.:
 - Sectoral reallocations (Criscuolo, 2022)
 - Firm dynamics and creative destruction (OECD, 2023; Calvino et al., 2022)
- Following the shock, firms had to reorganise their production processes and their interaction with customers and suppliers
 - Acceleration in the adoption and use of digital technologies and teleworking practices (Brynjolfsson et al., 2022; Bloom et al., 2023; EIB, 2022)



This work

- Focuses on the links between digital transformation and gaps among firms over the COVID-19 pandemic
- Explores these links using novel data with great detail on the type of digital technologies used and wide country coverage
 - Novel network methodology to account for potential hierarchical patterns in digital adoption
- Patterns of digitalisation during the pandemic
- Diffusion of key digital applications



DATA AND METHODOLOGY



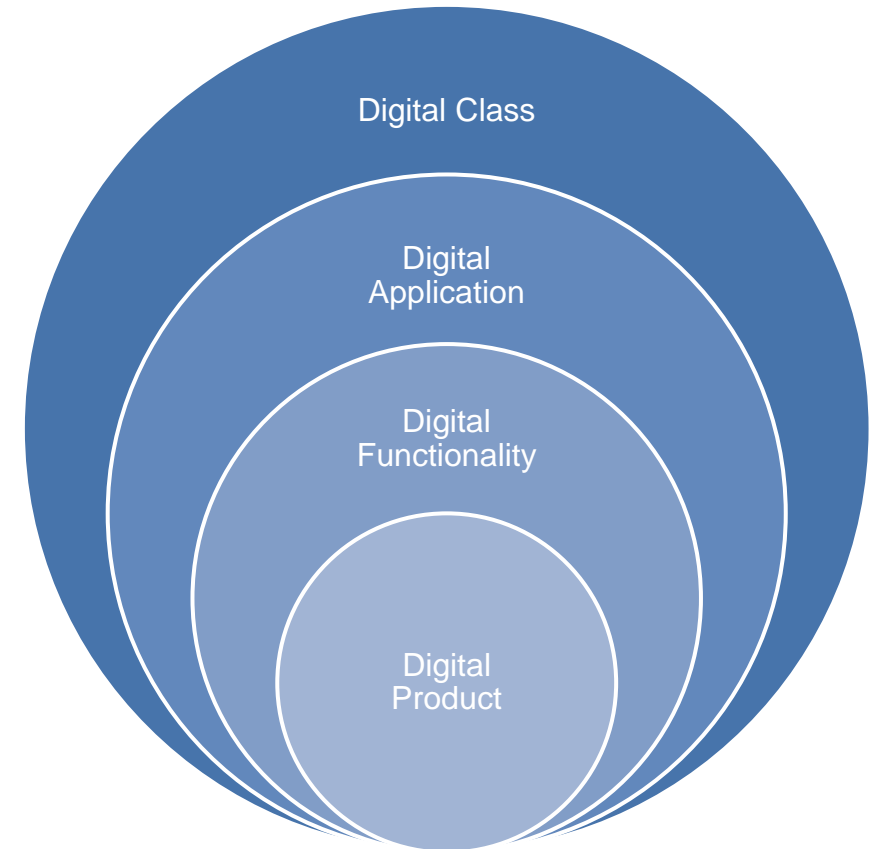
Data

- Commercial database from the Spiceworks Ziff Davis Aberdeen Group (formerly known as Harte-Hanks)
 - Reports basic financials and related information at the plant level (e.g., employment, turnover, sector, country, and presence of IT staff)
 - Collects **unique detailed information on IT and digital usage at the plant level**
 - IT budget spending and technology totals
 - Detailed information on the digital products installed (e.g., name of product, functionality, first date of adoption)
 - The database has been extensively used for economic analysis by a number of **empirical papers** (e.g., Bresnahan et al., 2002; Brynjolfsson and Hitt, 2003; Bloom et al., 2012; De Stefano et al., 2017; De Stefano, Kneller, and Timmis, 2018; Cao and Iansiti, 2022)
 - Years: 2019, 2020, 2021
 - 20 countries in Europe: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Hungary, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, the United Kingdom



Technology classification (I)

- Information on **digital products**
- Each product has information on related digital functionality
 - 179 digital functionalities
- Further classification in:
 - **23 digital applications**
 - **5 digital classes**





Technology classification (II)

	Digital classes				
Digital applications	<p>IT systems</p> <ul style="list-style-type: none">• IT architecture• IT development• Web architecture• Data management• IT security	<p>Digital Sales</p> <ul style="list-style-type: none">• Digital Commerce• CRM and Sales software• Customer Service• Marketing and Advertising	<p>Digital workplace</p> <ul style="list-style-type: none">• Collaborative software• Cloud• Publishing and Design software• Suites and SaaS	<p>Adv. app. analytics</p> <ul style="list-style-type: none">• Machine Learning• Big Data• A/B Testing• Analytics	<p>Bus./Industry soft.</p> <ul style="list-style-type: none">• Bus. Intelligence• HR mgmt.• ERP & Business mgmt.• Financial mgmt.• Supply Chain mgmt.• Industry software

- Classification consistent with similar research works in the literature
- Analyses robust to the use of different classifications



Methodology

– Linear probability model (LPM)

$$PI_i = \beta_0 + \beta X_{i,2019} + FE_{industry \times country} + \varepsilon_i$$

- PI_i is a dummy equal to 1 if plant i has introduced a new digital product during COVID-19
 - $X_{i,2019}$ is a vector of firm characteristics in 2019
 - Size, digitalisation, productivity, human capital, age, firm structure
 - $FE_{industry \times country}$ embodies (2-dig) industry-country fixed effects
- Model identifies associations and not causal relations

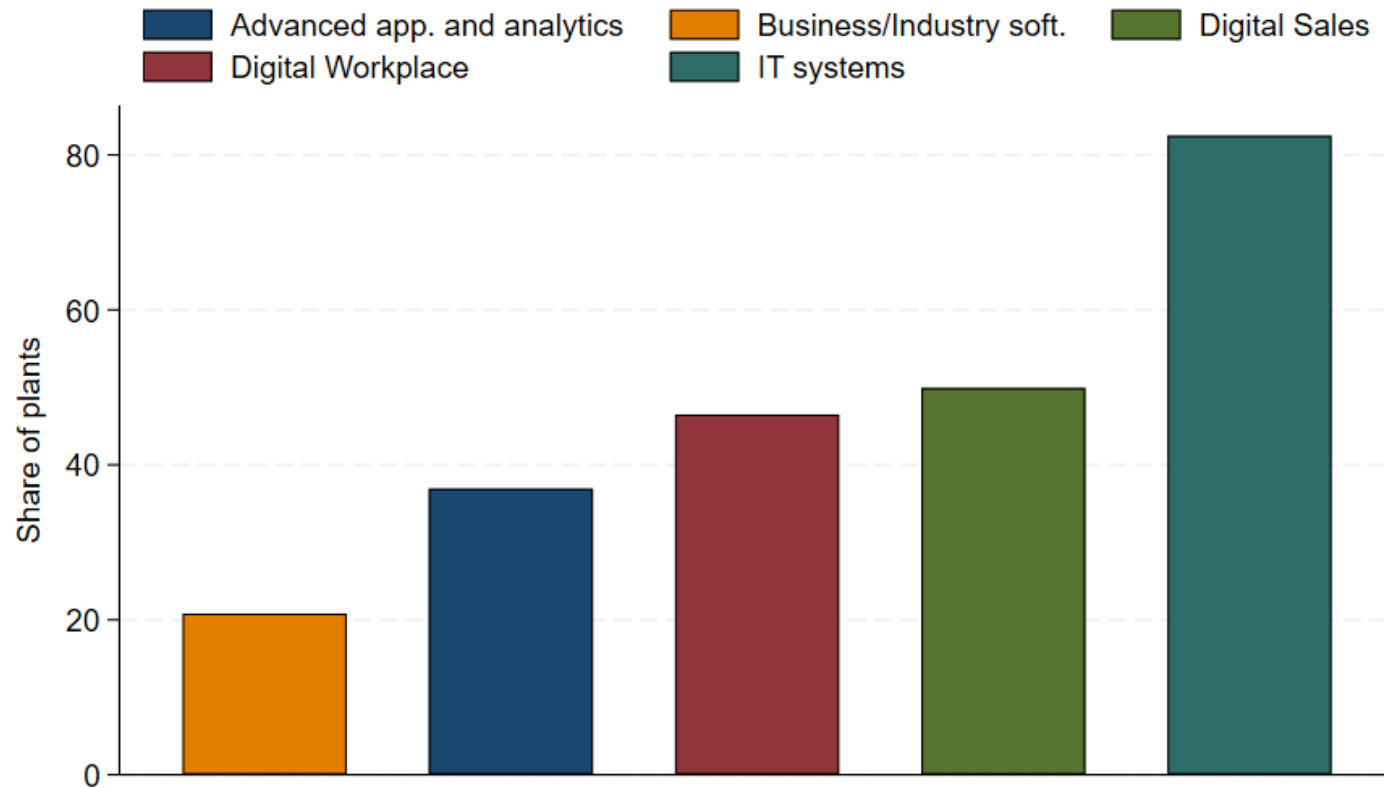


PATTERNS OF DIGITALISATION OVER THE PANDEMIC



A considerable share of firms introduced new digital products during the pandemic

Share of firms introducing new digital products during the pandemic across digital classes



Note: The figure displays the share of plants introducing new digital products (at least one product) during the pandemic, by digital technology class. The Figure reports results for the overall sample. Similar rankings are obtained focusing on specific countries or macro-sectors.

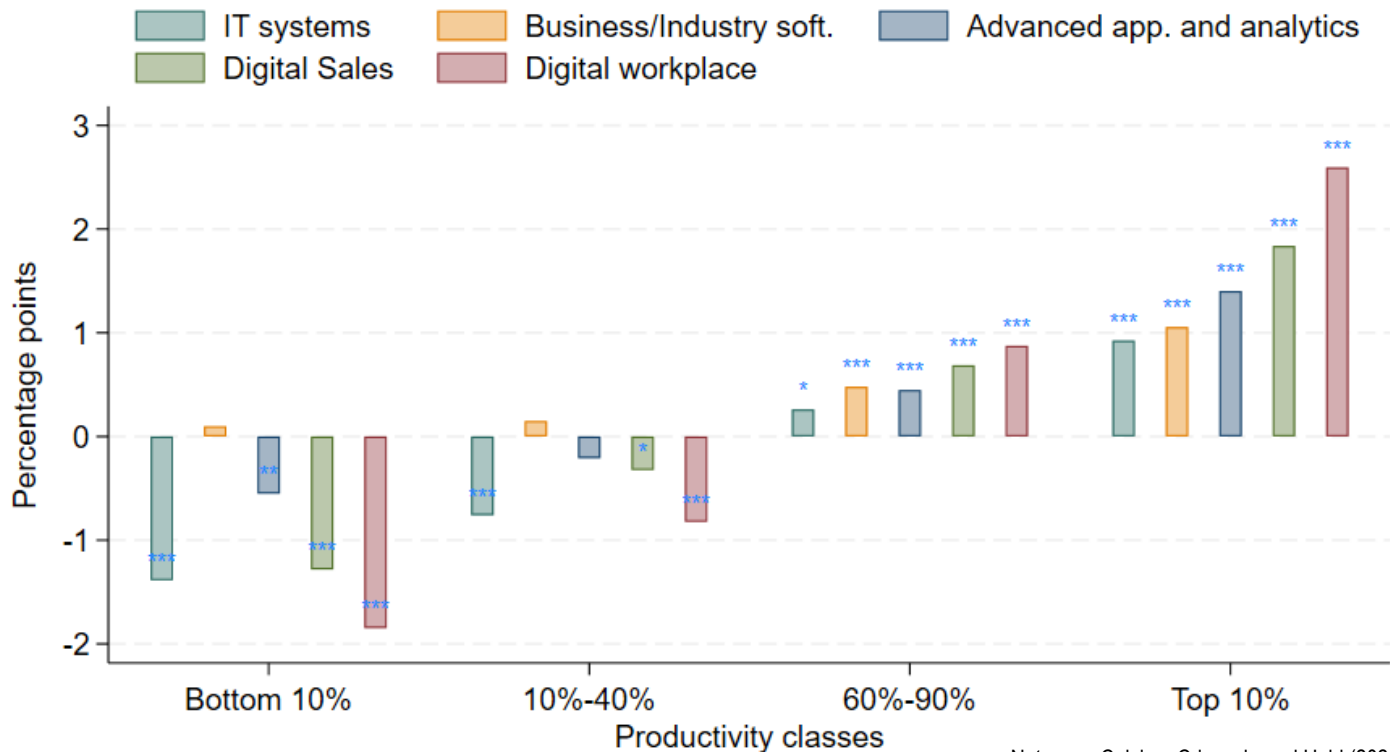
Source: Calvino, Criscuolo and Ughi (2024)

- Highest shares among firms introducing “IT systems”, “Digital sales” and “Digital workplace”
- Similar rankings across countries



Ex-ante more productive firms had higher probability of introducing new digital products during the pandemic

Firm productivity in 2019 and likelihood of introducing new digital products during the pandemic: regression coefficients for labour productivity classes, by digital technology classes
(reference productivity class: 40%-60%)



* p < .10, ** p < .05, *** p < .01

Note: see Calvino, Criscuolo and Ughi (2024).
Source: Calvino, Criscuolo and Ughi (2024)

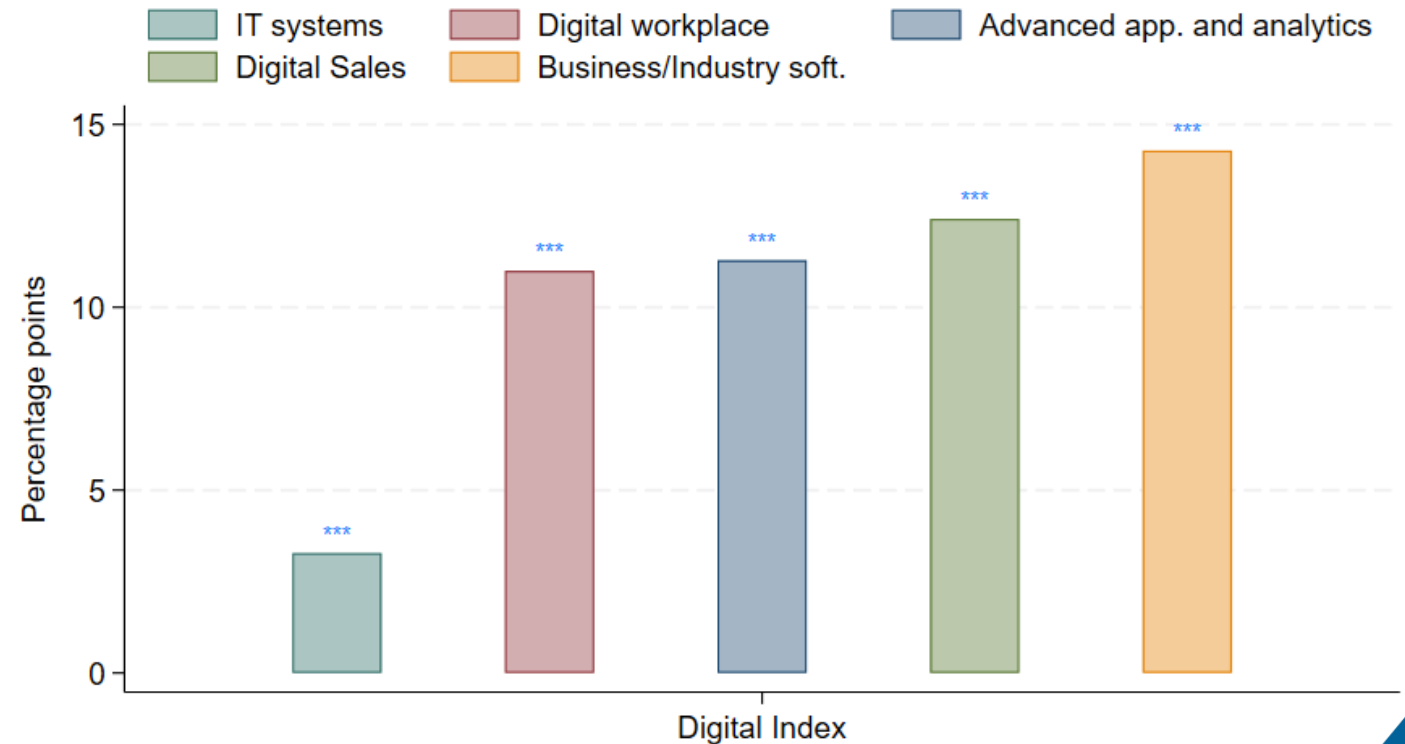
- Significant increasing association along the productivity distribution, across technology classes
 - LPM controlling also for size, age, human capital, digitalisation, firm structure, country-sector FE
- Robust to other specifications (e.g. Logit)



Ex-ante more digital firms had higher probability of introducing new digital products during the pandemic

- Digital index
 - $DI_i = \frac{n_i}{N_{c,s}}$
 - n_i is the number of digital functionalities for firm i
 - $N_{c,s}$ is the maximum number of functionalities available at the country-sector (2-dig) level
 - Index is then standardised (mean 0, s.d. 1)
- Positive and significant association across classes
 - LPM controlling also for productivity, size, age, human capital, firm structure, country-sector FE
- Overall robust to other specifications
 - Logit model
 - IT intensity variable

Firm digitalisation in 2019 and likelihood of introducing new digital products during the pandemic: regression coefficients for digital index, by digital technology classes



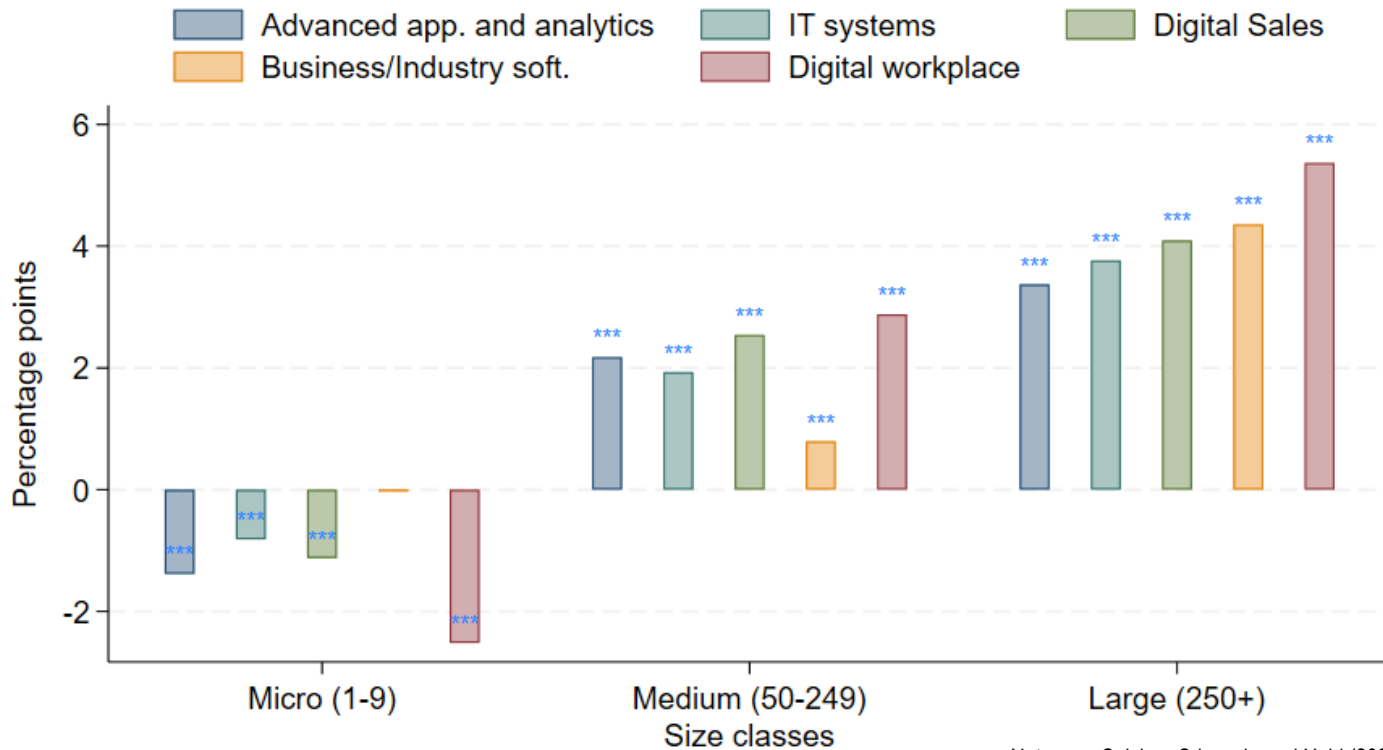
* p < .10, ** p < .05, *** p < .01

Note: see Calvino, Criscuolo and Ughi (2024).
Source: Calvino, Criscuolo and Ughi (2024)



Ex-ante larger firms had higher probability of introducing new digital products during the pandemic

Firm size in 2019 and likelihood of introducing new digital products during the pandemic: regression coefficients for size classes, by digital technology classes
(reference size class: 10-49)



* p < .10, ** p < .05, *** p < .01

Note: see Calvino, Criscuolo and Ughi (2024).
Source: Calvino, Criscuolo and Ughi (2024)

- Significant increasing association w.r.t. size, across technology classes
 - LPM controlling also for productivity, age, human capital, digitalisation, firm structure, country-sector FE
- In line with result about MNEs and multi-plant domestic firms
- Robust to other specifications (e.g. Logit)



Going digital over the pandemic: other results

- Age:
 - younger firms more likely to introduce new digital products (especially those in the class 6-10 years)
- Sectors:
 - firms in more advanced sectors (high-tech manufacturing and knowledge intensive services) more likely to introduce new digital products
- Human capital:
 - to some extent, firms equipped with IT staff more likely to introduce new products
- Additional robustness: regression results generally hold also at the level of digital applications (i.e., for specific digital applications within digital classes)
- Further results: “first adoption” vs “digital upgrading”

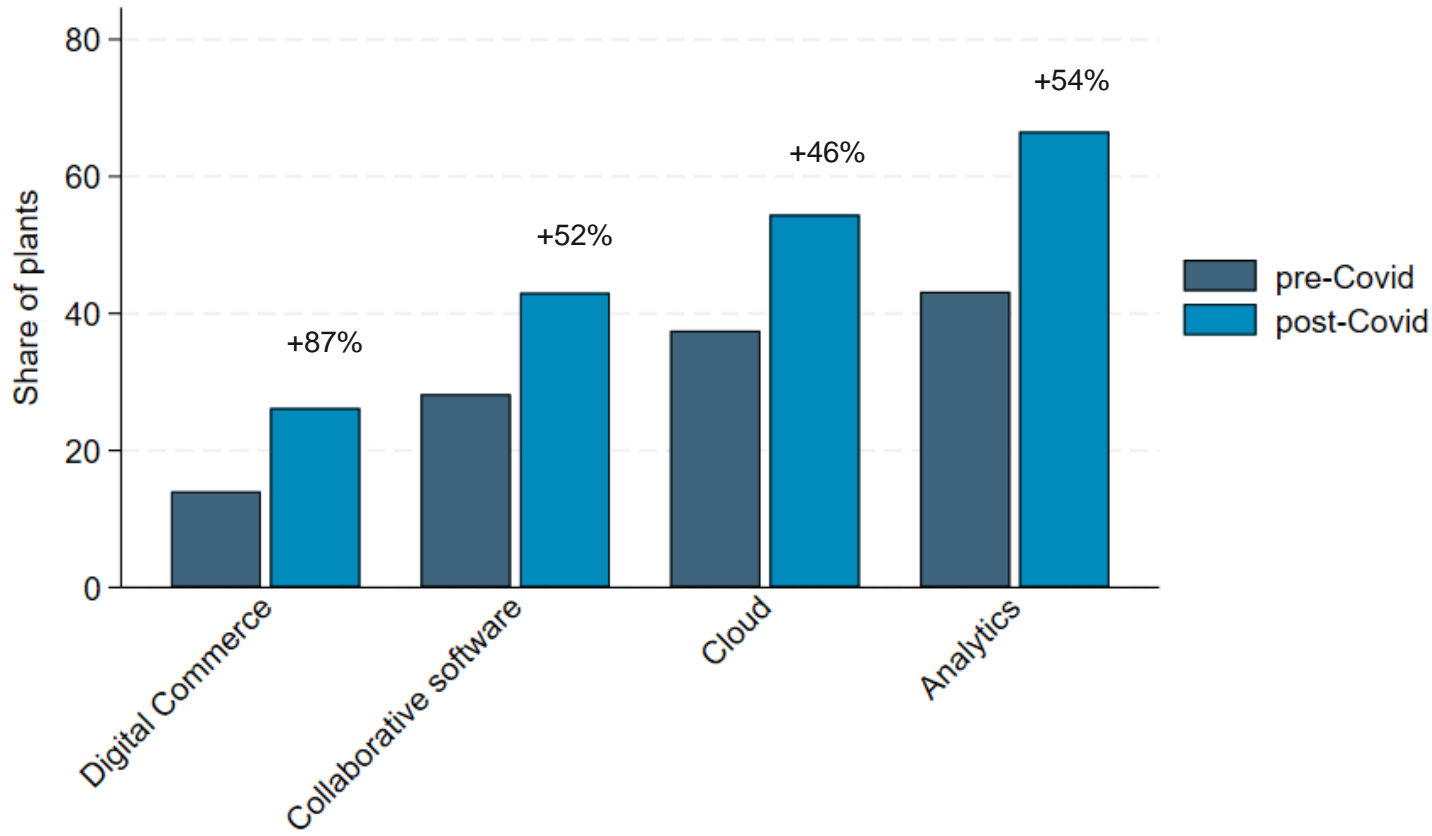


THE DIFFUSION OF KEY DIGITAL APPLICATIONS OVER THE PANDEMIC



Which digital applications were adopted the most over the pandemic?

Share of firms by top adopted digital applications, pre- and post-Covid



- Focus on *first* adoption
- Analytics, Cloud, Collaborative Software, Digital Commerce
- Findings in line with the literature (Riom and Valero, 2020, 2021; EIB, 2022; DeStefano and Timmis, 2023)

Note: The Figure displays the four digital applications that were adopted the most during the pandemic, by the cumulative share of plants having the given application before (2019) and after (2021) COVID-19. Applications that diffused the most are defined as those with (i) the highest growth in the cumulative number of plants having (adopted) the given digital application (end of 2021 vs end of 2019) and (ii) a share of diffusion of at least 10% during the pandemic years. The bars (pre- and post-Covid) are ordered w.r.t. the share of adoption. In the Figure, "Digital Commerce" is the digital application with the highest growth in diffusion (+87%), followed by "Analytics" (+54%), "Collaborative Software" (+52%), and "Cloud" (+46%). Results refer to the overall sample of firms, i.e., are computed across sectors and countries.

Source: Calvino, Criscuolo and Ughi (2024)



Research questions

1. Has ex-ante digitalisation shaped the adoption of “Analytics”, “Cloud”, “Collaborative Software”, “Digital Commerce” over the pandemic?
2. Were these applications adopted in bundles with other technologies?



Related literature

- The adoption of digital technologies may have a sequential hierarchical pattern, with more sophisticated technologies adopted only after more basic applications (Zolas et al., 2020)
- Relatedly, digital technologies are often used in bundles rather than in isolation (Cho et al., 2023)



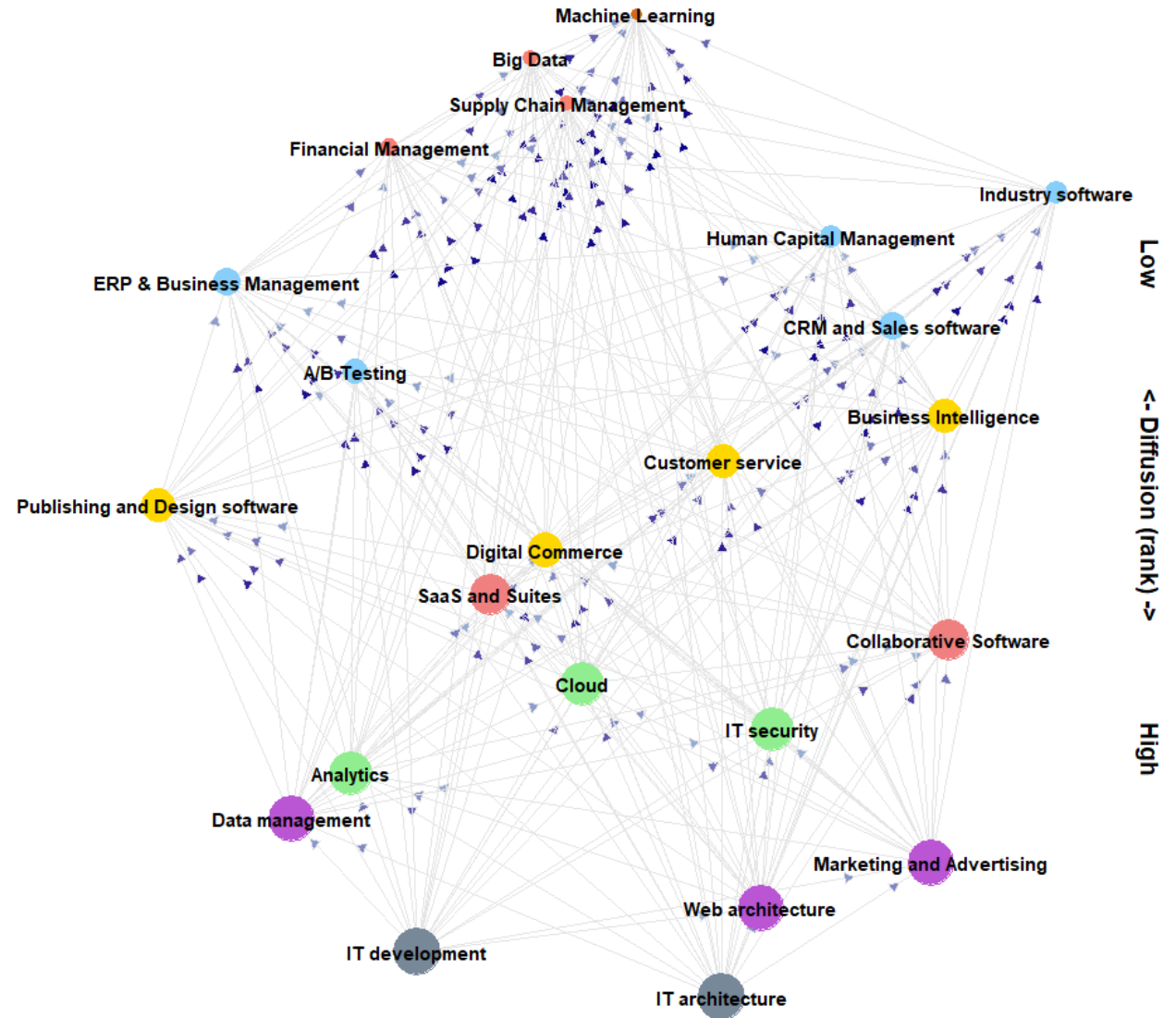
Methodology

- The work builds on this literature and contributes with a novel methodological approach: a network analysis tailored on digital technologies
 - Network analysis has been increasingly applied (e.g. Hosseinioun et al., 2023, focusing on labour force skills)
- The analysis aims at disentangling potential hierarchical patterns in the use of digital applications
 - Information on digital applications in 2019



Network analysis

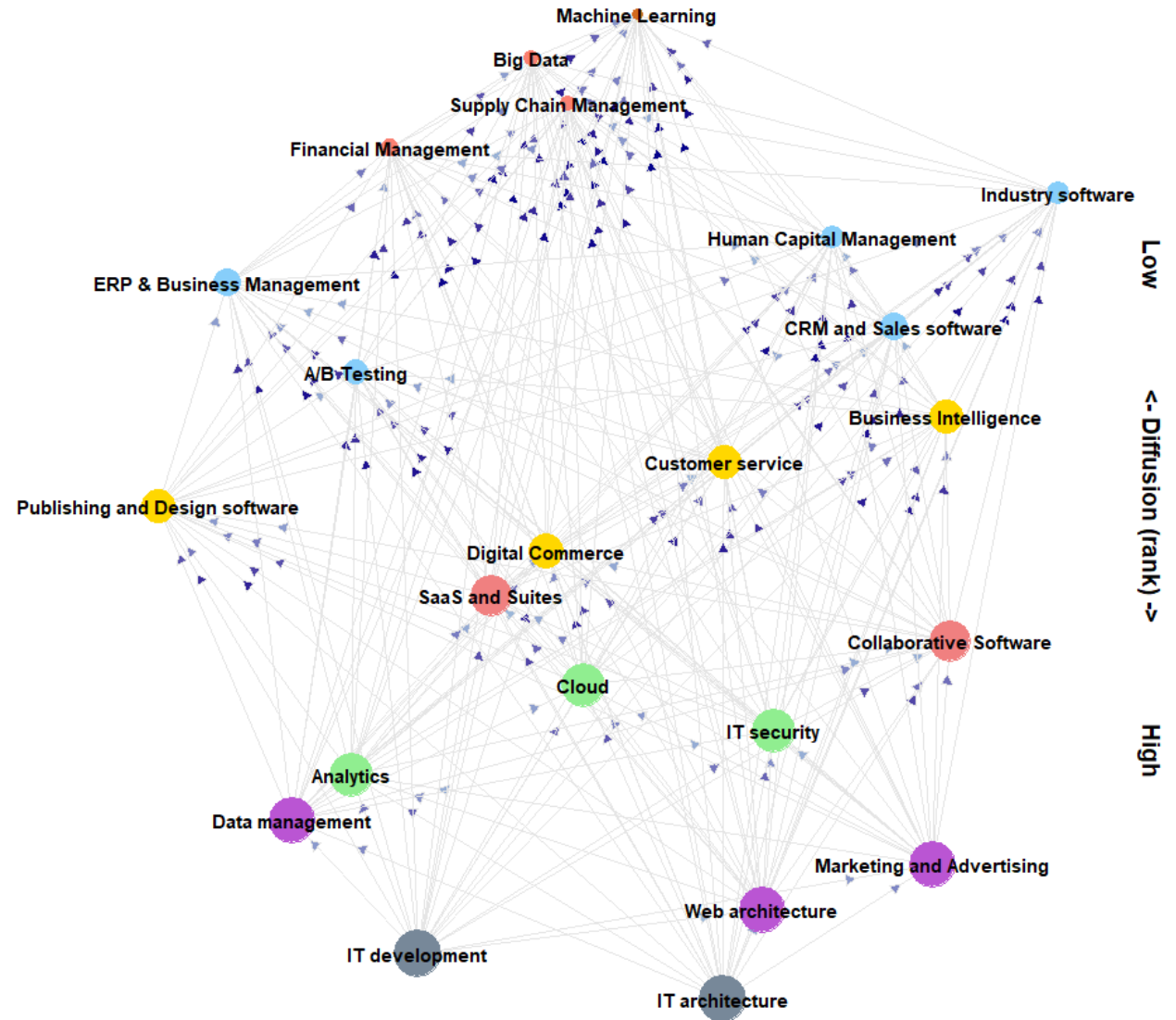
- Each node represents a digital application





Network analysis

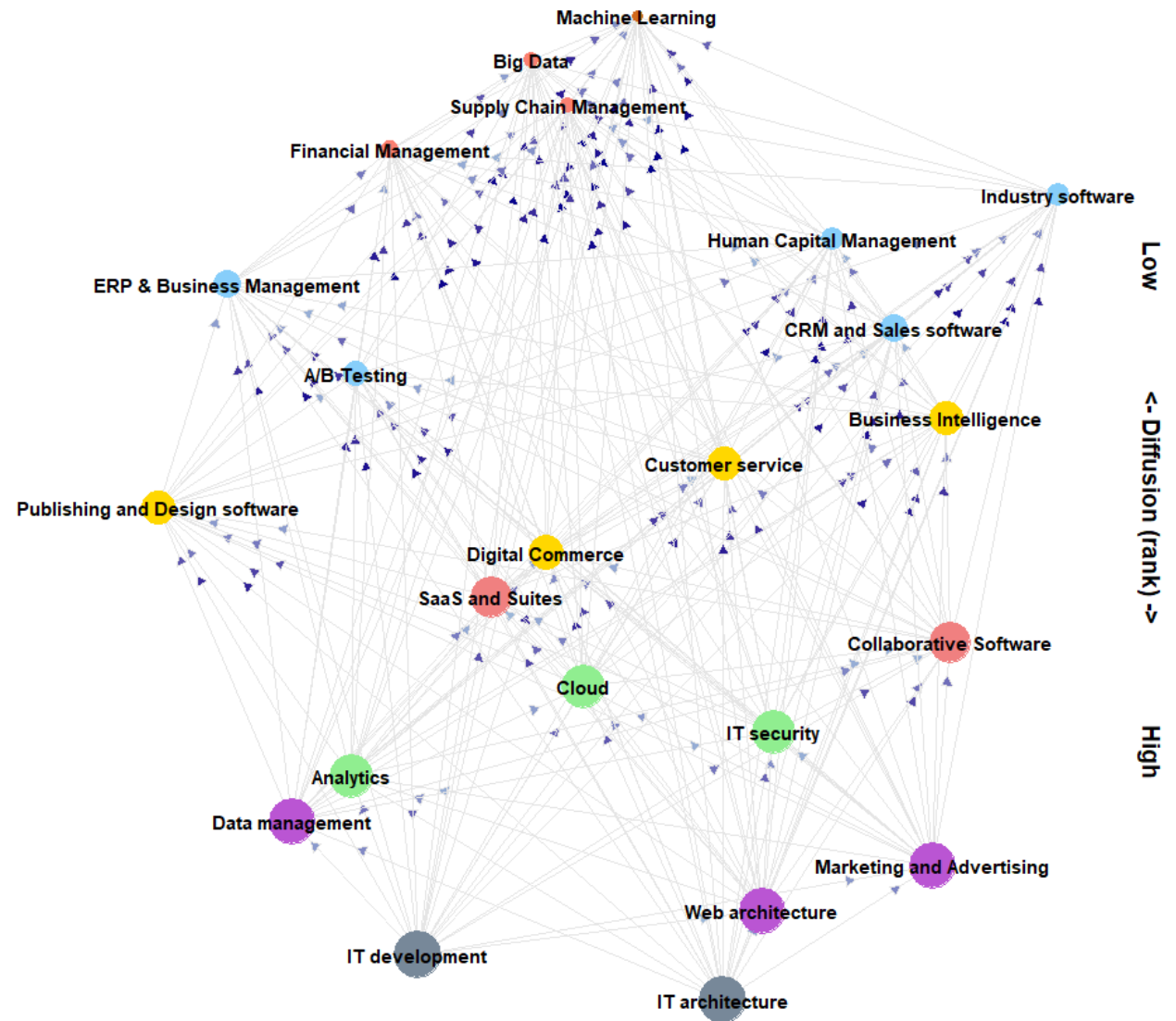
- Each node represents a digital application
- Node ranking (y-axis) represents diffusion
 - Top nodes, low diffusion
 - Bottom nodes, high diffusion





Network analysis

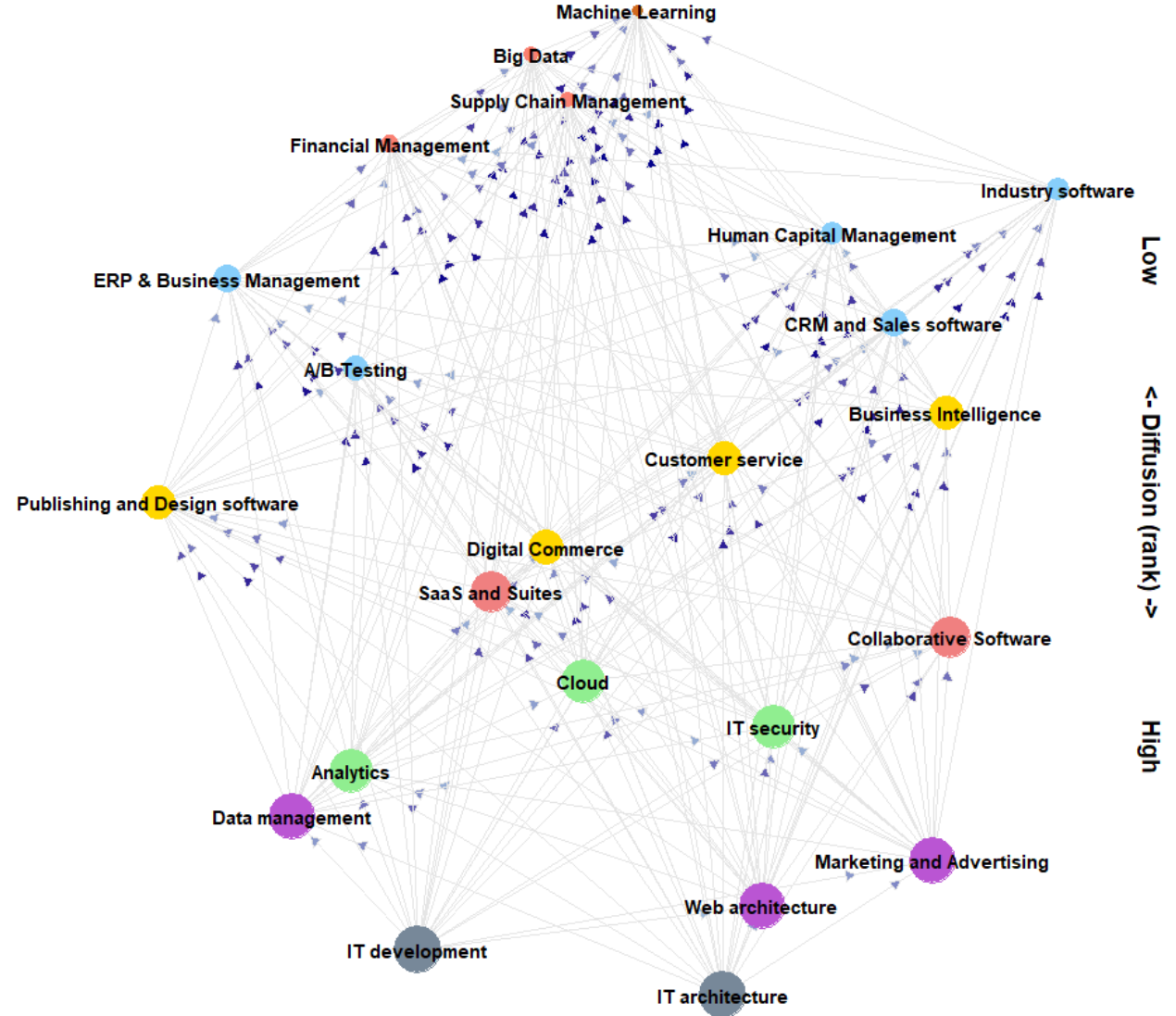
- Each node represents a digital application
- Node ranking (y-axis) represents diffusion
 - Top nodes, low diffusion
 - Bottom nodes, high diffusion
- Edges between any two nodes represent co-occurrences
 - Firms have both applications





Network analysis

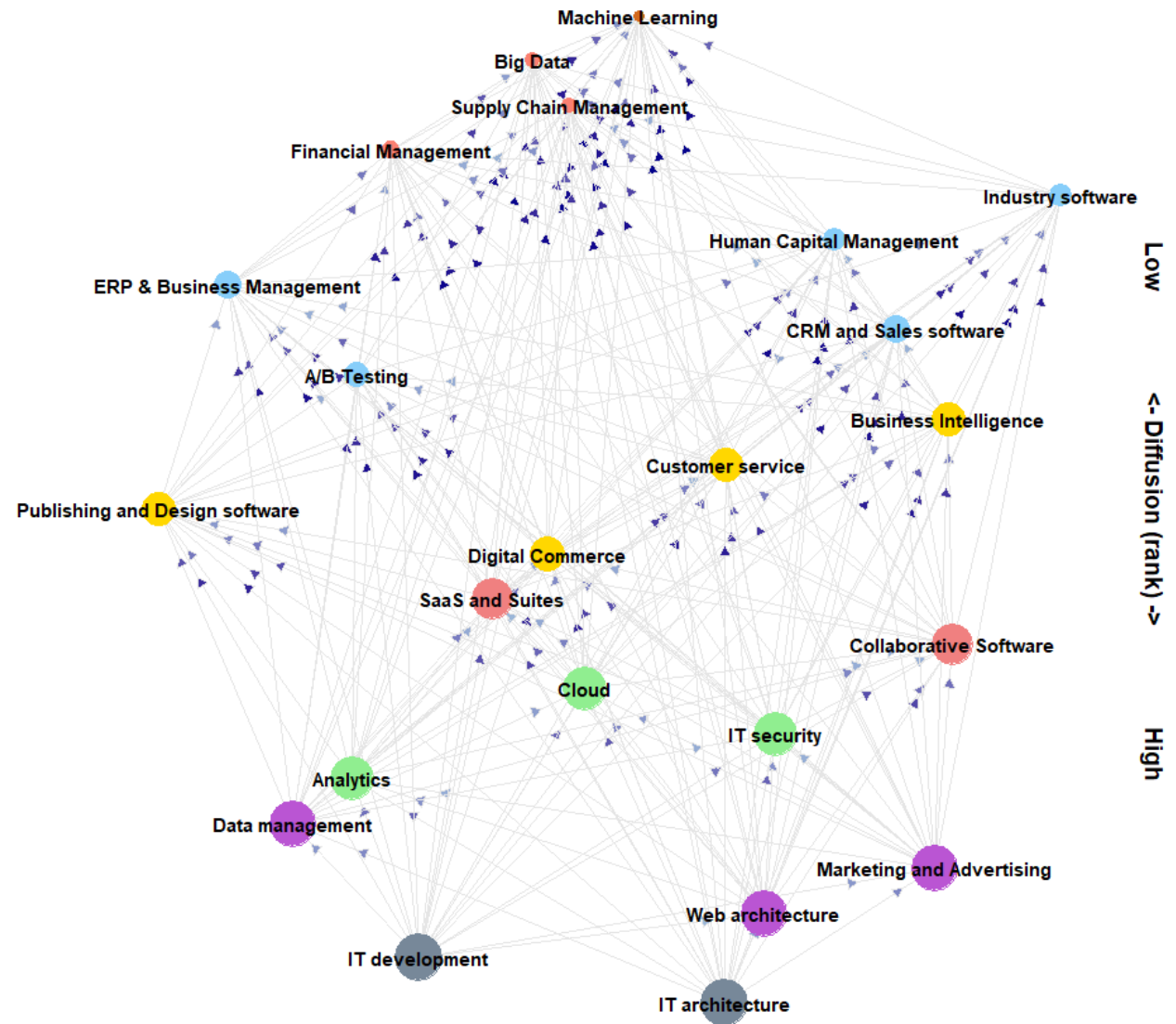
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- Directed edges represent differences in conditional probabilities
 - Weight of the edge is the strength of the directed relation





Network analysis

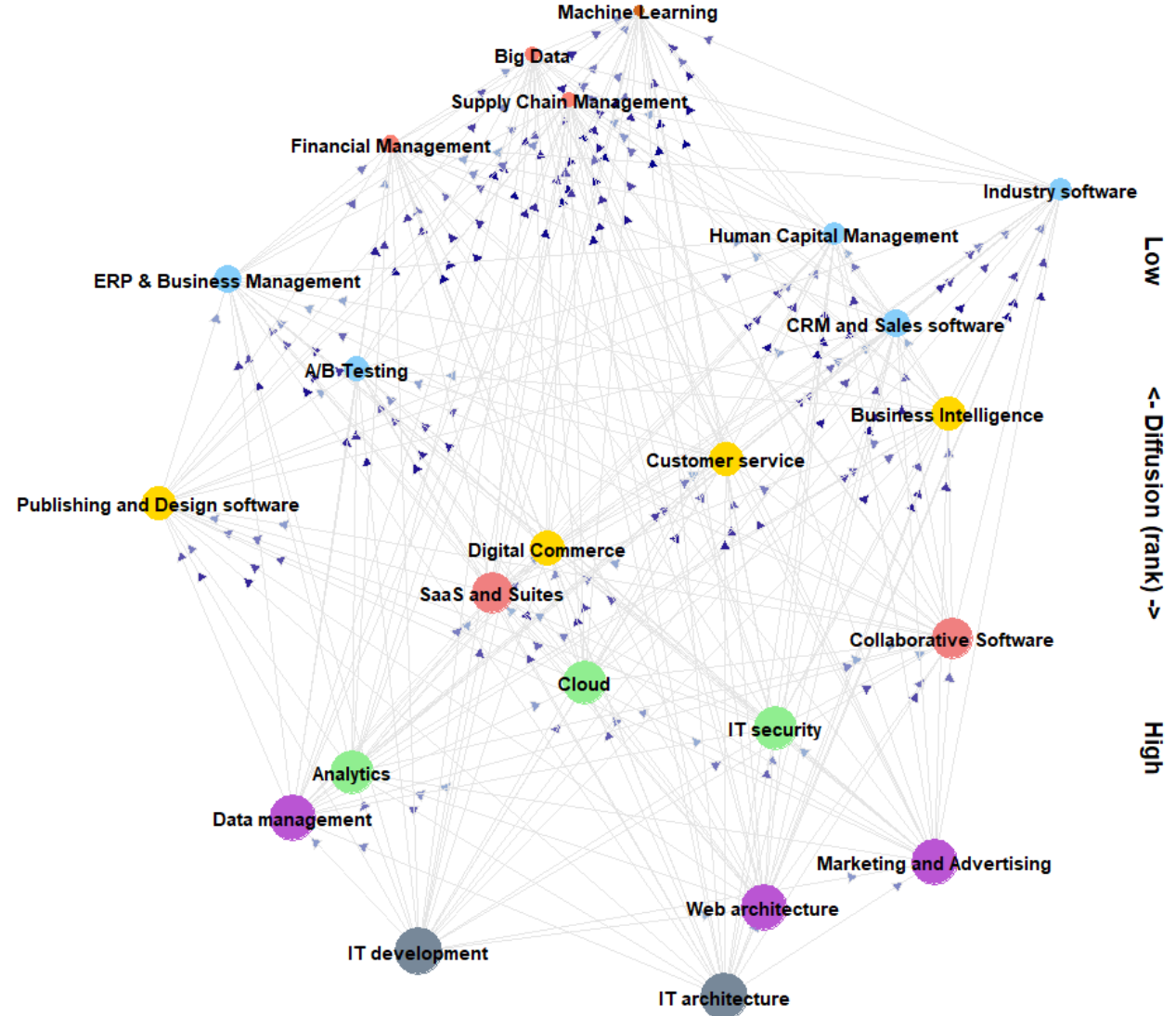
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 - Weight of the edge is the strength of the directed relation
- Size of the circle
 - Larger if higher number of *outward* edges
 - Smaller if higher number of *inward* edges





Network analysis

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- Node ranking (y-axis) represents diffusion
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 - Weight of the edge is the strength of the directed relation
- Size of the circle
 - Larger if higher number of *outward* edges
 - Smaller if higher number of *inward* edges
- Color of the circle:
 - similar level of diffusion and same inward edges

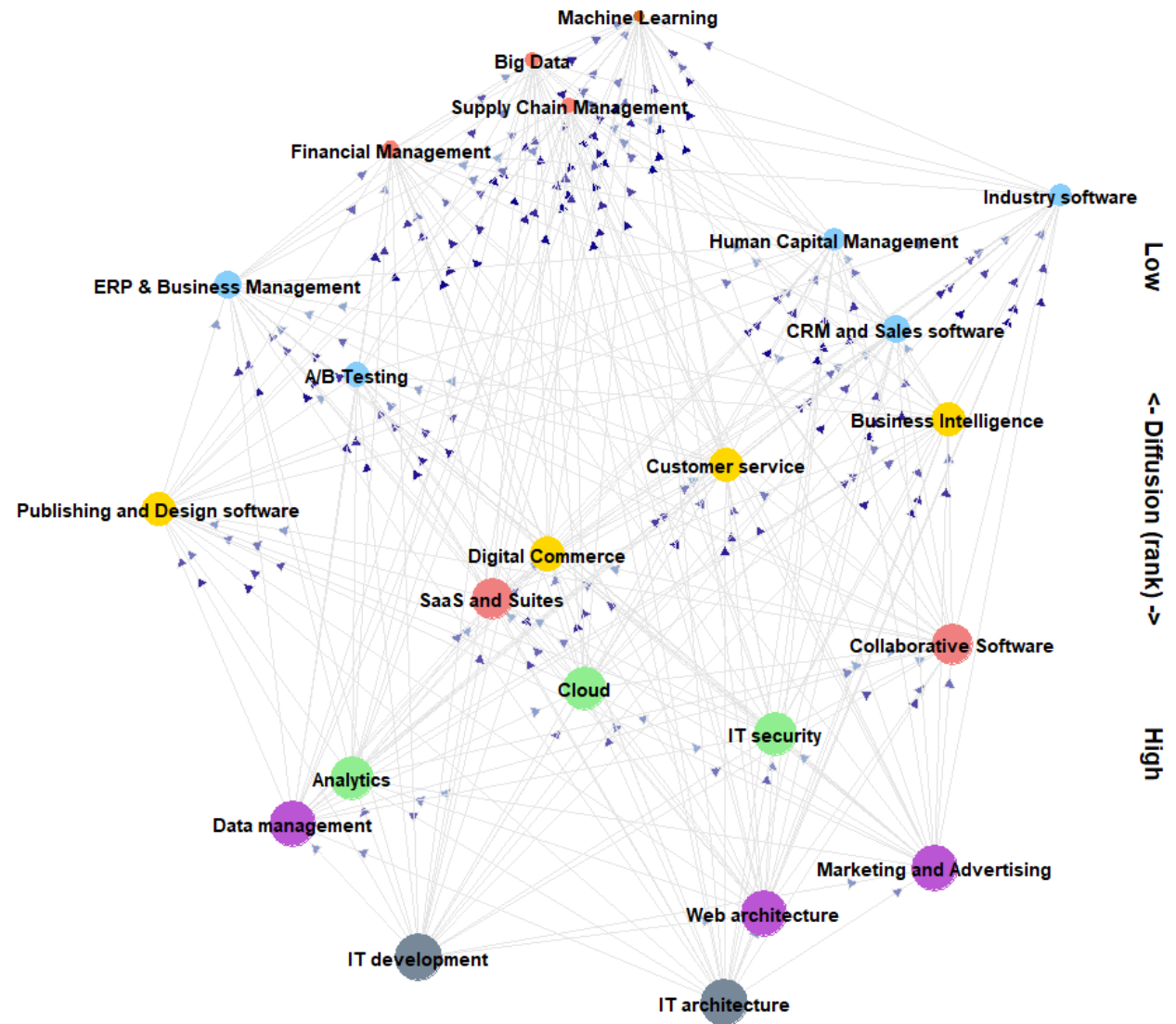




Network analysis

For each digital application, the analysis identifies

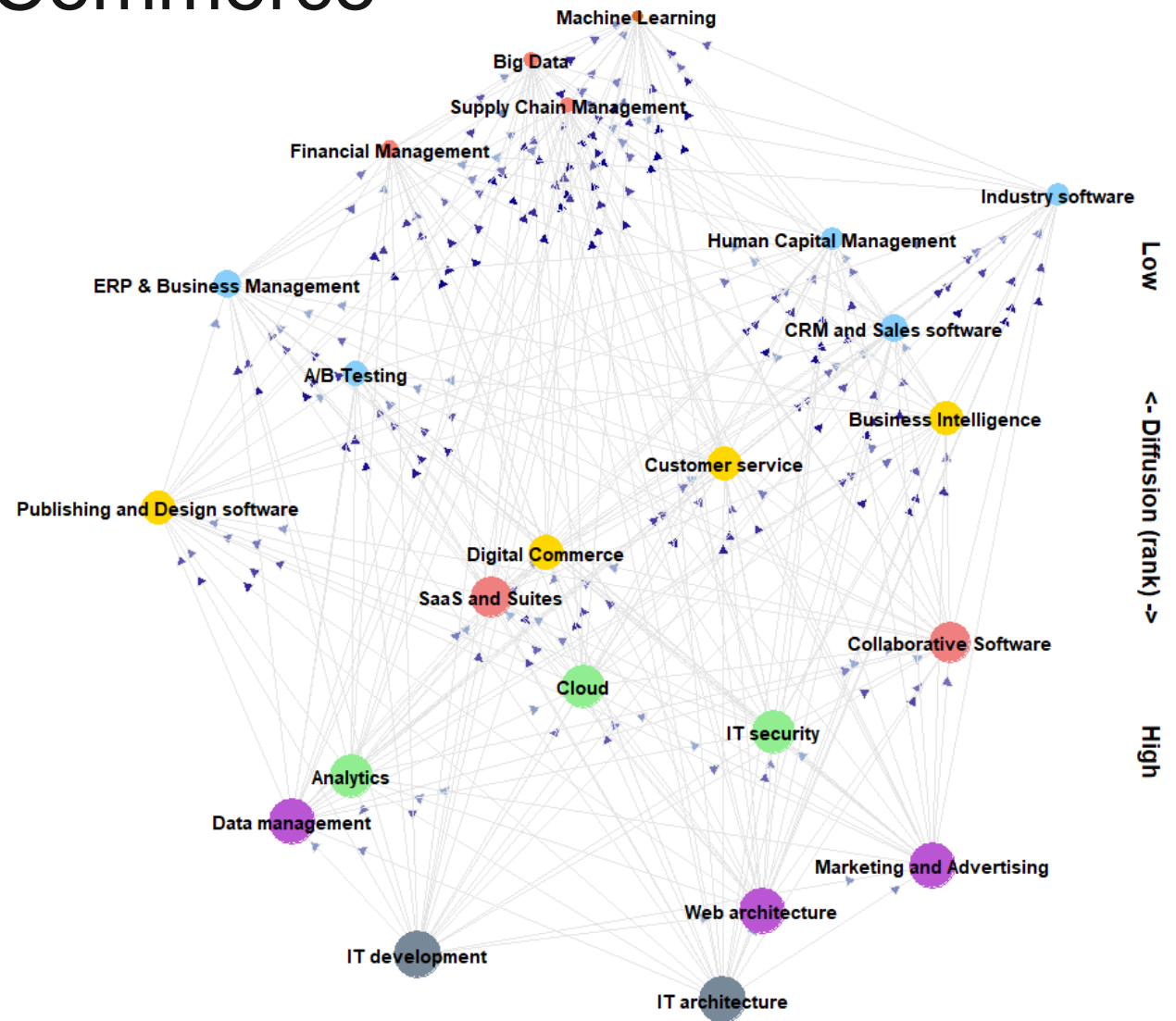
- *Supporting* applications: those connected to the focal application with inward edges (hierarchical relation)
- *Horizontal* applications: those with similar levels of diffusion and same inward edges





Example for Digital Commerce

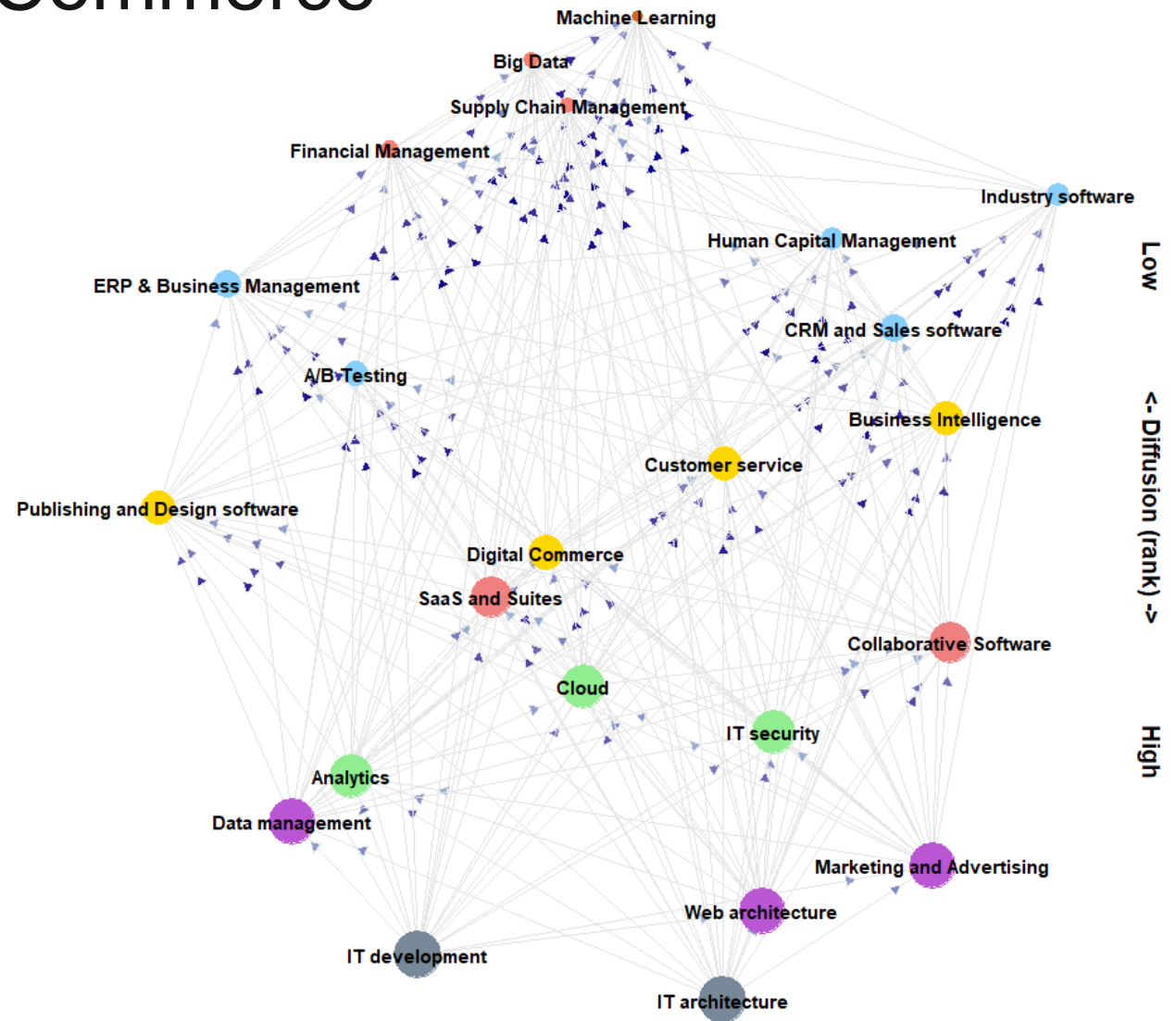
- 10 supporting applications
 - IT architecture
 - IT development
 - Web architecture
 - Marketing and Advertising
 - Data management
 - IT security
 - Cloud
 - Analytics
 - Collaborative Software
 - Suites and Software as a Service





Example for Digital Commerce

- 3 horizontal applications
 - Customer Service
 - Business Intelligence
 - Publishing and Design software





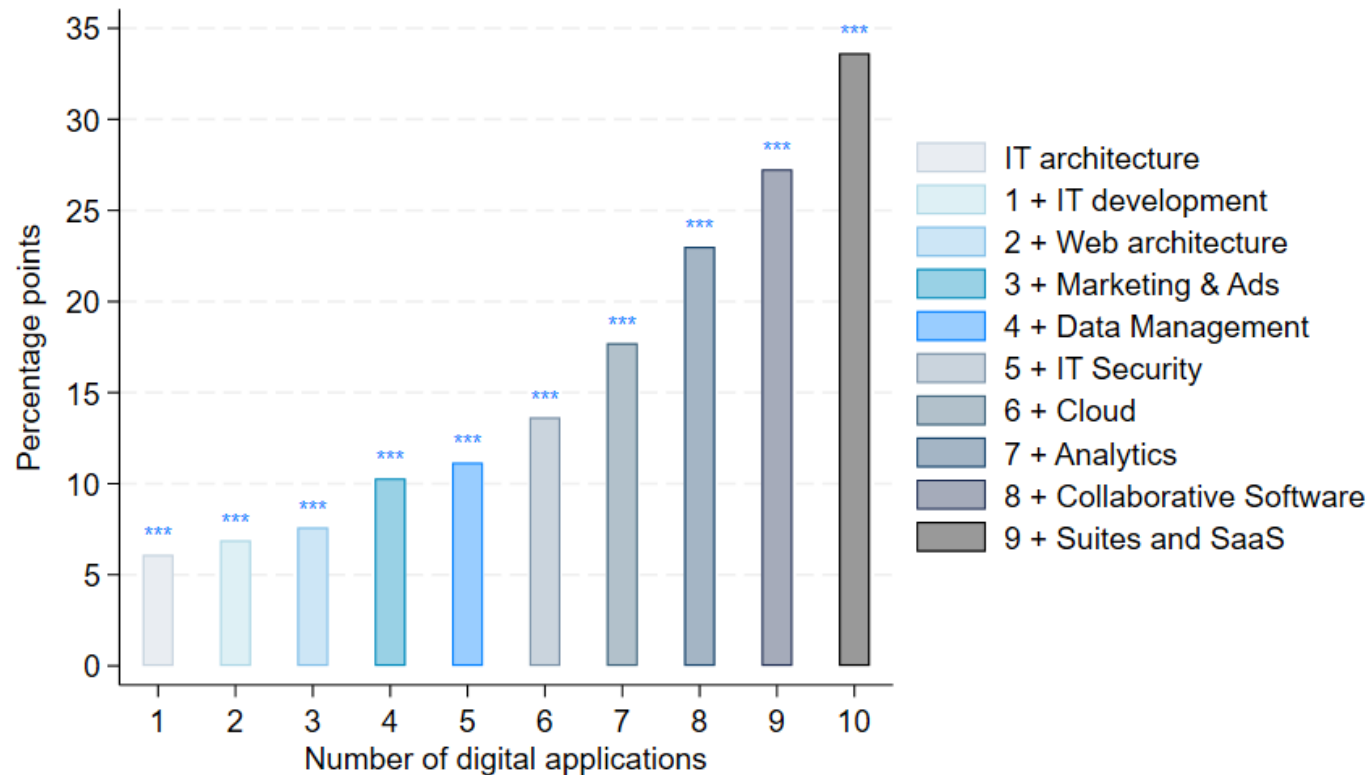
Research questions

1. Has ex-ante digitalisation shaped the first adoption of “Analytics”, “Cloud”, “Collaborative Software”, “Digital Commerce” over the pandemic?
 - Role of supporting applications
2. Were these applications adopted in bundles with other technologies over the pandemic?
 - Role of horizontal applications



Role of supporting technologies: Digital Commerce

Number of supporting technologies pre-pandemic and probability of adoption of Digital Commerce during the crisis



* p < .10, ** p < .05, *** p < .01

- Positive and significant association: higher probability of first adoption with supporting technologies
- Increasing with the number of supporting technologies

Note: The figure displays the relation between a firm's number of complementary supporting technologies (in 2019) and the probability of adoption of "Digital Commerce" during the pandemic. Each bar reports the estimated coefficient of a linear probability model that employs the Digital Commerce adoption dummy as dependent variable and includes the digital dummy for supporting technologies, productivity, size and age classes, firm structure, and presence of IT staff as main independent variables. The digital dummy for supporting technologies is defined as 1 if the firm in 2019 had the given set of technologies, 0 otherwise (Model 1: IT architecture; Model 2: IT architecture and IT development; Model 3: IT architecture and IT development and Web architecture, etc.). Each regression includes 2-digit sector-country fixed effects and employs robust standard errors. Source: Calvino, Criscuolo and Ughi (2024).



Exploratory evidence on bundles: Analytics, Cloud, IT Security

**Adoption in bundles over the pandemic:
Cloud, Analytics and IT Security**

Dependent variable → Independent variable ↓	Cloud	IT Security	Analytics
Cloud		0.21***	0.14***
IT Security	0.22***		0.16***
Analytics	0.11***	0.13***	
Supporting tech. (2019)	Yes	Yes	Yes
Firm characteristics (2019)	Yes	Yes	Yes
Country-sector FE	Yes	Yes	Yes

Note: see Calvino, Criscuolo and Ughi (2024).
Source: Calvino, Criscuolo and Ughi (2024)

- First adoption during COVID-19
- Positive and significant association: for each dyad, higher probability of first adoption if also another horizontal application is adopted
 - LPM controlling also for size, age, human capital, supporting technologies, firm structure, country-sector FE (in 2019)
 - Results robust to the exclusion of supporting technologies (in 2019)



Conclusions

- Pre-existing gaps (e.g., digital and productivity ones) among firms have played an important role in firms' ability to react to the COVID-19 crisis and in introducing new technologies
 - The applied network methodology helped uncover relevant insights about the role of ex-ante digital capabilities and adoption in bundles
- Different likelihoods of digital adoption across different groups of firms, coupled with heterogeneous returns to adoption, might result in increasing divergences
- Policy makers can play a key role for fostering an inclusive digital transformation
 - Critical areas for policy attention include:
(i) human capital; (ii) digital capabilities; (iii) digital infrastructure; (iv) business-friendly framework conditions



THANK YOU

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