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# Rethinking the digital transformation in knowledge-intensive services: A technology space analysis

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A B S T R A C T

The world is in the midst of a digital transformation. An intensified prevalence and use of digital technologies is fundamentally changing organizations and economies. However, the notion of 'digital transformation' is both theoretically and empirically underspecified. This paper rethinks the digital transformation narrative theoretically by embedding the concept in concurrent debates about technological revolutions and neo-Schumpeterian innovation theory. Empirically, the paper specifies the digital transformation by analysing the technological composition of key start-up and scale-up companies in the knowledge-intensive services sector. Undertaking a technology space analysis of 40,754 start-up and scale-up companies derived from the near real-time Dealroom.co database, we analyse which technologies and application domains are currently converging, distilling of key elements of the digital transformation. The paper concludes that the transmission of digital technologies is often indirect through 'key enabling technology clusters' that connect the technological vanguard to application domains.

## The digital transformation: a pervasive but underspecified concept

In 2015, the World Economic Forum launched the 'Digital Transformation Initiative' based on the premise that this digital transformation could 'unlock a 100 trillion dollars for business and society'. The initiative aims to mobilize incumbent corporations in grasping an accelerating technological transformation based on 'digital technologies' that is changing how people live and work (World Economic Forum, 2018). Between 2015 and 2021, the number of academic publications dealing with said digital transformation has approximately doubled yearly, from 58 during 2015 to 3380 in 2021.[1] As a foundation of economic progress, the digital transformation is argued to be radically reshaping economies (World Economic Forum, 2018), a claim shared by overlapping narratives about a 'fourth industrial revolution' and the emergence of '4.0 technologies' (Laffi and Lenzi, 2021). This paper advances new insights about the digital transformation, drawing on an innovative analysis of technology spaces to understand the contributing roles of different technologies in the process.

Despite the allure of the digital transformation narrative, many companies are investing in basic technologies rather than in the alleged digital transformation centrepiece technologies, such as Artificial Intelligence (AI), Robotics and the Internet of Things (IoT) (Mugge et al., 2021). Vial (2019) notes that notwithstanding the widespread enthusiasm about the digital transformation, only about 10% of studies surveyed formally define the phenomenon. Moreover, Vial (2019) points out that these definitions are inconsistent and characterised by a lack of conceptual clarity, and that the term 'digital technologies' that underpins the phenomenon is taken for granted. Where the academic debate focuses on how organizations might leverage, implement or harness the digital transformation, what exactly 'the digital' is remains opaque (Gray and Rumpe, 2017; Vial, 2019). While there are several

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[1] Search in www.scopus.com on "digital transformation" (complete phrase) in title, abstract and keywords. Date of search: 5 March 2022.

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candidate technologies that are argued to be at the heart of the digital transformation, there is not a strong consensus about how to define and demarcate the relevant key components (Capello and Lenzi, 2021). The World Economic Forum (2018, p. 7), for example, singles out several technologies, including: AI; Autonomous Vehicles; Big Data Analytics; Cloud Computing; Custom Manufacturing and 3D Printing; IoT and Connected Devices; Robots and Drones; and, Social Media and Platforms. However, several commentators have remarked that the list could easily be extended backwards to include innovations emerging from the Internet over the last two decades (Fernández-Rovira et al., 2021; Lee and Lee, 2021; Vial, 2019); or even over older Information and Communication Technologies (ICT) revolutionary moments (Barras, 1990). In this study, we advance new insights about those elements of digital transformation that are both genuinely novel while also being a continuation of the ongoing ICT general purpose technology (Brynjolfsson and McAfee, 2014).

The starting point of our analysis is that the concept of digital transformation is theoretically and empirically underspecified. Theoretically, the digital transformation needs to be aligned with, but also distinguished from, parallel narratives around a 'fourth industrial or technological revolution' (Laffi and Lenzi, 2021). The knowledge-intensive services were commonly considered as the 'sectoral vanguard' throughout the ICT-driven technological revolution from the 1960s onwards (Barras, 1990; Frank et al., 2019). Consequently, from the perspective of this sector, casting the current deepening of ICT-driven transformation again as an 'industrial revolution' (Martinelli et al., 2021) seems off. Therefore, this paper specifically studies knowledge-intensive services as case to understand the latest developments in order to separate hype from genuine change compared to that earlier period (Cetrulo and Nuvolari, 2019). Empirically, properly identifying the key elements of the digital transformation is hampered by inertia in the taxonomy of technologies and industries as embodied in patent data or industrial classification codes. As technologies converge and sectors coalesce, the innovation frontier shifts, rendering older sectoral and technological taxonomies obsolete. Patent data are suboptimal to follow technological change in real time, given patents' time lag and how digital technology patents are dominated by filings from large corporations (Ménière et al., 2017). By extending the technology space analysis of Boschma et al. (2015) and Whittle and Kogler (2019), the paper examines industrial and technology categories relationally to alleviate the empirical underspecification. Our extension to the technology space approach comprises using near real-time data based on the Dealroom.co dataset and stochastic blockmodeling techniques to create aggregated dynamic technology clusters. The near real-time data also provides a complementary start-up and scale-up perspective, as these companies, particularly in the knowledge-intensive services, may not be patent-orientated (Delgado and Mills, 2020).

Our argument is developed as follows. Section two addresses the theoretical underspecification of the digital transformation by situating the concept in the Neo-Schumpeterian tradition. After addressing the conceptual ambiguities, concurring with Perez (2010), we consider the digital transformation a distinct techno-economic paradigm within the longer ongoing ICT revolution. Section three introduces how the use of graph-analytical methods and near real-time datasets can be used to build technology spaces of related and unrelated technologies, which provide the roadmap of the possibilities within the technological trajectory. Section four then details how we operationalize building a technology space using near real-time datasets, before section five presents the finding and provides an in-depth analysis of the technological composition of the digital transformation in the knowledge-intensive service sector, thus alleviating the issue of empirical underspecification. In section six, we conclude by reflecting on the main analytical and methodological contributions, and identifying directions for future research.

## Theoretical underspecification: situating the digital transformations in the neo-Schumpeterian tradition

When studying the digital transformation, one quickly arrives at a paradox. Some raise the suggestion that society is on the dawn of a 'fourth industrial revolution'. This revolution has been gathering steam since the mid-2010s and relates to the merging, or fusion of digital, biological, and physical worlds, giving rise to automation and use of new technologies that are transforming the way we work and live (Martinelli et al., 2021; Philbeck and Davis, 2018). However, for others, the emphasis on information technology suggests that the digital transformation is best understood as an intensification and, in some respects, the culmination of the ICT revolution that commenced in the 1950s of the last century (Brynjolfsson and McAfee, 2014; Lee and Lee, 2021; Wessel et al., 2021). Castells (1997) predicted that the 'information age', which he regards as centred around ICTs, would be accelerating in the 21st century. And from this perspective the recent wave of digital innovation is a culminating testament to ICT being a worthy successor in the lineage of the steam engine, electricity, and the internal combustion engine as an epoch-defining general purpose technology (Brynjolfsson and McAfee, 2014). However, given the ongoing ambiguity and oscillating pace of technological change associated with this longer term perspective on digital transformation, there is merit in adopting a more nuanced approach.

The prevailing digital transformation can be understood as a 'new phase' in a technological revolution driven around ICT's in the Neo-Schumpeterian evolutionary theory of innovation (Dosi, 1982; Freeman, 1994). The digital transformation is then the latest episode of a longer ongoing fifth technological revolution (Perez, 2010). Each episode within the fifth technological revolution defines a cluster of innovations around a key ICT technology – what Freeman (1994) calls a 'technology system'. According to Perez (2010), previous ICT technology systems were based around microprocessors, personal computers, software, and the Internet. Each of these episodes represents a change in a techno-economic paradigm whereby new technologies transformed industries.

The advent of a new techno-economic paradigm contributes to the movement along the technological trajectory, culminating in new products, services and even industries. Digital transformation is also characterised by more frequent recombinant innovation whereby new combinations of technologies are exploited. These could be new combinations of closely related technologies but change accelerates when rare but revolutionary unrelated technologies are combined into new developments (Castaldi et al., 2015; Frenken et al., 2012). Technological convergence (Teece, 2018) and sector coalescence (Hendrikse et al., 2020) sees previously distinct industries and unrelated technologies interact. The most salient example is when the historically distinct sectors of 'information' and 'communications' technologies coalesced into the 'ICT sector' during the 1970s and 1980s (Freeman, 1987, cited in Dicken, 2011, p. 80). From this perspective, the current digital transformation can be regarded as a similar episode of recombinant innovation and sector coalescence. As this recombinant innovation happens within the technological field we define as ICT, this paper presents a more finely grained empirical analysis to understand what is recombining and coalescing exactly.

## Operationalizing the digital transformation in knowledge-intensive services

### *Mapping techno-economic trajectories using topological spaces*

As technological trajectories evolve, 'new combinations' (Schumpeter, 1934 [1912]) of knowledge drive innovation. However, not all combinations are equally likely to emerge and neither are all combinations equally transformative. Radical innovations might prompt the emergence of whole new industries and redefinitions of existing ones, and the digital transformation exemplifies this with a technology system based on innovations in AI, Mobile Technologies, Digital Platforms, and Cloud Computing. Given the rapidly evolving technological trajectory, labelling ICT as a general purpose technology is too generic and a more refined analytical language is needed to empirically decode the interplay between these technology system components. Capello and Lenzi (2021), following Ménière et al. (2017) suggest that distinguishing between 'core technologies', 'enabling technologies', and 'application domains' is useful to understand recombinant innovation. A more refined analysis requires identifying the 'key enabling technologies' that build bridges between the old and the new (Antonietti and Montresor, 2021; Teece, 2018) and facilitate technological convergence and sector coalescence. To address the empirical underspecification of the digital transformation concept, we need to identify these technology types (core, enabling and application), and their relations, within the emerging technology system. That is, which core technology connects to which application domain via which enabling technology?

Such a relational perspective can be achieved by analysing topological spaces based on two-mode network analysis (Engelsman and Van Raan, 1994; Hidalgo et al., 2007; Kogler et al., 2017; Neffke et al., 2011). The degree of relatedness between technologies is approximated by making co-occurrence matrices of technologies on patents, industries, products, or skills in a firm. These topological spaces are respectively called 'knowledge space', 'industry space' or 'skills space' depending on the kind of data that is used as input (Whittle and Kogler, 2019; Hidalgo, 2021), or overarchingly just called 'technology space' (Boschma et al., 2015). To construct a technology space, co-occurrences of knowledge categories in, for instance, patent documents (idem) are counted, and then used to estimate relations between these categories (Whittle and Kogler, 2019). The result is an affiliation network (Borgatti and Halgin, 2011), where nodes are the respective technology categories, and ties represent weighted relations between these categories. A set of standardized measures subsequently allows valuing the relatedness between these categories (Hyung Joo and Kim, 2009). Subsequent network-analytical measures such as clustering and centrality values can then be used to identify substructures in the network.

However, heeding Allen's (1994) warning that the technological evolutionary process might change the categories of technological identity themselves, we embrace Dosi's (1982, pp. 151-152) definition of technology that includes knowledge, industry, skills, and products. As the digital transformation unfolds, what initially was a technological category (e.g., natural language processing algorithms) can become a building block of products, and ultimately transform and become namesake of an industry as companies specialize. To accommodate this notion of changing categories and an agnostic standpoint towards the self-reported industry and technology 'tags' that define our data source (see Section 4), we adopt the overarching term 'technology space' for our topological space analysis. Nodes in the technology space can refer to industries, knowledge, skills, markets or products and it is the data-driven analysis that groups them into larger wholes that we call 'technology clusters'.

### *Start-ups in the knowledge-intensive services: the vanguard sector of the digital transformation*

This study focuses on the digital transformation in knowledge-intensive services. While our analysis is also bound to computational limits that compel some sectoral demarcation, the choice for knowledge-intensive services is underpinned by the sector's historical relevance for the adoption of ICTs (Hall, 2011). The argument that ICT is central to a service-based technological revolution has been around since at least the late 1970s (Brynjolfsson and McAfee, 2014; Quinn, 1988). Advanced, or 'professional', services have been previously characterized by their aggressive exploitation of advanced information technology (Moulaert and Djellal, 1995), and have long been recognized as one of the most technologically dynamic parts of the economy (Quinn, 1988). According to Barras (1990), it was the professional services that were the 'vanguard sector' in the initial adoption of ICT technologies in earlier phases of the ICT technological revolution. Barras (1990, p.231) also rather prophetically argued that it would 'take 'decades' until the full potential of [...these ICT...] technological possibilities can be realized'. Frank et al. (2019) confirm Barras' hunches when they argue that the digital transformation induces an ever-deepening 'servitization' of the economy. Additionally, Barras (1990) predicted that, contrary to previous technological revolutions, start-ups in the professional services would increasingly become relevant at the later stages in the diffusion of ICTs when costs of data processing dropped. In the financial sector, the rise of FinTech has been characterized as one of the leading application domains of AI and related technologies (Lai and Samers, 2021), where start-ups indeed play a key role in pushing the technological envelope (Hendrikse et al., 2018; Hendrikse et al., 2020). Following FinTech, there has been a spawling proliferation of the suffix '-Tech' in the talk about the digital transformation (LegalTech, RegTech, HealthTech, MusicTech, EdTech). These technological developments spawned a huge opportunity structure for digital entrepreneurship and new entrants to established service markets (Nambisan, 2017) to explore the new combinations in the coalescing sectors. Thus, studying the proliferation and trajectory of start-ups in the sphere of knowledge-intensive services allows us to generate a detailed map of the digital transformation.

## Building a technology space using near real-time datasets

### *Near real-time datasets*

Previous analyses of technology spaces have been heavily reliant on patent data (Balland and Boschma, 2021; Kogler et al., 2017). However, patent data has drawbacks that can obscure the full picture of technological change. Patent data imposes a categorical taxonomy on the data that may conceal processes of sector coalescence where industry identities transform. While patents selectively represent the technological frontier, they miss the adoption of already existing technologies in new application domains (OECD, 2005). Moreover, not all innovations are patentable (Griliches, 1991) and thus patents may not reflect the complete application domains of a technology (Dernis et al., 2016). In general, the process of patenting is long, and creates inherent lag between patent application/granting and actual industry usage of the studied innovations, which also make it difficult to track the emergence and coalescence of technologies in rapidly innovating industries (IPO UK, 2019). More so, patent data studies on digital technologies show that the 'Big Tech' firms are the majority recipients of digital technology related patents (Ménière et al., 2017), largely masking the potential contributions of start- and scale-ups. In knowledge-intensive services, the limitations mentioned above are more significant, as patent-based business models are not the common way to create a competitive advantage (Delgado and Mills, 2020), and many businesses are based around smaller scale client-orientated work (Cordasco et al., 2021).

To alleviate the drawbacks of patents and similar data sources, we concur with Kinne and Lenz (2021) that we need to harness the data-analytical innovations central to the digital transformation to map the transformation as it unfolds. The growing affordability of computation power, data bandwidth, and Big Data availability, gave rise to new data platform service companies that track the digital presence of companies in near real-time. Using web crawler and natural language processing technologies, near real-time data platforms mine companies' online digital footprints, and collate the evolution of these footprints, populating dynamic databases. By using a tagging system, companies can be classified into any combination of industries, technologies, business models and as the companies evolve, the classification evolves with them. New insights gleaned from such data add depth and narrows time gaps of reporting trends. The platform's data-driven taxonomy offers a dynamic representation of both the adopting application domain and the most up-to-date technologies and business models used. This paper utilizes the Dealroom.co[2] near real-time data platform. Dealroom.co has a relatively large coverage of start-ups and has recently seen wider adoption in academic studies (e.g., Bradley et al., 2019; Dellermann et al., 2017).

Alongside their advantages, near real-time data sources also generate new analytical challenges. First, Dealroom.co does not exclusively collect data on start-ups but focuses on them, providing a complementary perspective to the large corporations that dominate patent databases (Ménière et al., 2017). Second, validity of the analysis is contingent on the ability of the data company's algorithms to capture digital footprints, raising issues of comprehensiveness. To study the extent of some of these limitations, Dalle et al. (2017) compared OECD Entrepreneurship Financing Database with near real-time data platform Crunchbase and found good coverage for new ventures in the US and Europe suggesting validity issues are limited in these contexts. Third, the nature of the Dealroom.co data relies primarily on multiple automated self-coded 'tags', describing the economic sector, technology and/or market of companies in the dataset. This reliance on self-reporting could introduce bias in the dataset. Our analysis uses the tags as exported from the database with minimum intervention, such that the sheer number of observations mitigates potential imprecisions of self-reporting bias. Although these caveats might qualify the validity of our findings, the use of near real-time dataset is nevertheless promising compared to the shortcomings of other established indicators such as patents.

*Constructing the dataset*

Our dataset of start-up and scale-up companies was harvested from the Dealroom.co platform in April 2020. We used Dealroom.co's search engine to mine the data, which allows filtering companies based on different characteristics, including industry and technology tags found in companies' profiles. In order to demarcate a sample of companies that are active in the digital transformation in knowledge-intensive services we set filter criteria to omit companies unrelated to the purpose of this study (see Appendix 1, for an elaboration).

The harvesting resulted in a worldwide dataset of 40,754 companies. At the moment of data harvesting, Dealroom.co had a clear underrepresentation of some geographical areas, particularly in Asia-Pacific, which has been a prominent location for the digital transformation in knowledge-intensive services (Lai and Samers, 2021). To detect other possible caveats on the data coverage, we compared Dealroom.co and Crunchbase datasets (extracted in similar procedures), and the results demonstrated similar patterns of sectorial and geographical distribution (with most of the companies located in North America and Europe) in both datasets.

From the 40,754 companies, 4542 different tags were extracted. These tags comprise not only industries and technologies, but also products and markets, however, without strict taxonomic boundaries between these types of tags. We first cleaned up the tags by recoding acronyms to match with full word tags, i.e., AI to Artificial Intelligence; DApp to Decentralized applications, etc. In this process, a total of 209 tags were removed. Second, because of the significant computational power necessary to analyse networks of this size, we removed all tags that interlocked less than 40 companies (less than 0.1% of the total companies in our sample). Resultantly, a total of 694 tags were retained.

To build the network projection, the $n$ tags that describe the technological relations between $m$ companies are used to build an adjacency matrix B with companies in the rows and tags on the columns (Fig. 1. – Step 1). A cell in the matrix was assigned the value '1' when company $i$ has a tag $j$. The bipartite graph was transformed into a unipartite network via projection (Fig. 1 – Step 2) by multiplying the matrix B by its

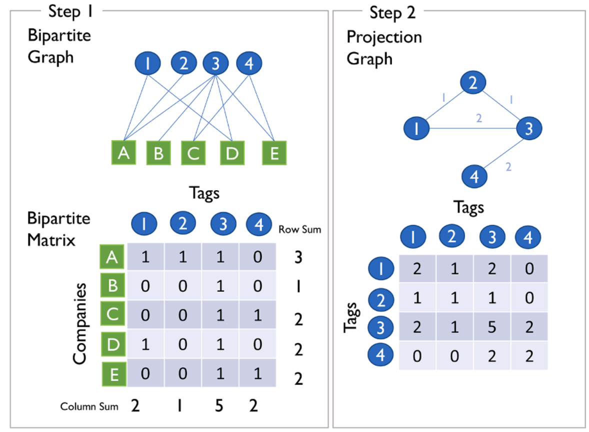


**Fig. 1.** Building a Bipartite (Step 1) and projection graph (Step 2).

transpose, $P = BB'$ (Borgatti and Halgin, 2011). The result is a $n$ x $n$ symmetric square matrix $P$, where the rows and columns represent the tags (columns) in B, and a cell $P_{ij}$ contains the number of tags shared by companies $i$ and $j$ for i,k. Cell $P_{ii}$ contains the number of companies associated with tag $i$, i.e., the diagonal cells of the projection matrix indicate each tag's total occurence

The bipartite projection of the start-ups' tags generates the representation of a topological space (see Fig. 1– Step 2). Nodes in this network are specific tags. Edges in this network correspond to the number of tag co-occurrences in companies in the dataset. The final dataset of 40,754 companies comprises 694 nodes and 17,237 edges.

*Data manipulation, pruning and visualization*

Our analytical approach is summarized in Fig. 2. Steps 1 and 2 are applied to the full network and networks at different time points, so in the latter case, we can visualize the digital transformation throughout the years. Steps 3 and 4 are applied only to the full network, so we can zoom in on the current relationships between technologies.

*Relatedness and technology space*

The first step to construct the technology space for the different networks is to calculate the relationship (i.e., relatedness) between the different tags. Although the co-occurrences of tags are our baseline to construct a measure of relatedness, these measures often are influenced by the frequency that these tags appear in the data. To alleviate this influence, we standardized the co-occurrences using a probabilistic measure of normalized relatedness (Balland, 2016; Boschma et al., 2015; Hidalgo et al., 2007). The probabilistic index (Steijn, 2021), a version of association strength (see Balland, 2017; Van Eck and Waltman, 2009), allows correcting the co-occurrences using combinations without repetition to calculate relatedness, thus providing a more accurate estimation of the relation between pairs of tags.

$$S_{ij} = \frac{C_{ij}}{\left(\frac{S_i}{T}\frac{S_j}{(T-S_i)} + \frac{S_j}{T}\frac{S_i}{(T-S_j)}\right)m}, \; i \neq j$$

In which, $C_{ij}$ is the value of the co-occurrences for $i$ and $j$, and $S_i$ and $S_j$ are the number of occurrences for $i$ and $j$ (i.e., the row sum or column sum of the co-occurrence matrix when the diagonal is zero). $T$ represents the total number of occurrences $\sum_{i=1}^{n} Si$ with $n$ being the total number of tags, and $m$ represents the total number of co-occurrences ($\frac{\sum_{i=1}^{n} Si}{2}$). The resulting relatedness values range from 0 to infinite, where a value higher than 1 indicates a deviation from statistical independence/randomness (van Eck and Waltman, 2009). Following Knuepling and Broekel (2020), we use the non-random edges (i.e., a relatedness value

[2] https://dealroom.co/

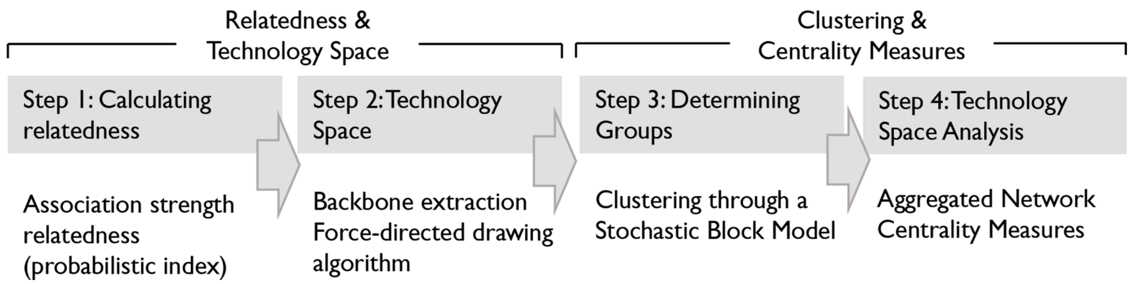


**Fig. 2.** Creating a technology space: Step-wise data analysis procedure.

higher than 1) for further analyses.

In a second step, we refine our analysis by calculating the most significant ties in the network using backbone extraction (Domagalski et al., 2021). Using the fixed degree sequence model (FDSM) (from the backbone package in R), we extracted the backbone structure from the transpose of the bipartite matrix of companies and tags. As a result, we identify the statistically significant edges, by testing the importance of the connection with respect to a random occurrence.

The significant edges are then fed into a visualization algorithm (Fruchterman-Reingold), using the package '*igraph*' (Csardi and Nepusz, 2006) for network visualization in R, which places more similar tags close to each other revealing the backbone structure of the technology space. The edges shown are the most significant connections between tags ($p$ <0.05), and tags are spaced depending of their degree of relatedness. Nodes thar are far apart in the technology space tend to be relatively unrelated, while more proximate nodes indicate relatedness (see Krempel, 2011).

*Clustering of technologies and technology space analysis*

We use two approaches to construct composite 'technology clusters' and their relations from our heterogenous collection of tags. First, using a Stochastic Blockmodel (SBM) we determine clusters of tags within the technology space. The SBM assign nodes with similar properties to specific clusters based on the relationships that the nodes have with other nodes in the network (Funke and Becker, 2019). The clusters, therefore, are organized such that the nodes' linking probability with other nodes in the network is the same as other nodes in their same cluster (Fortunato, 2010). The resulting structure is a classification based on the connectivity patterns of the nodes, and a probability value assign to each node that reflects the likelihood to belong to a cluster that includes other nodes with similar connectivity patterns in the network. Specifically, we use the Blockmodels package in R as the edge weights are 0 or 1, we choose a Bernoulli model (Leger, 2016).

The result of a SBM inference is not only a partition, but also a description of the relationship between the inferred clusters. Therefore, it is possible to identify links between clusters of tags. The optimal number of clusters is the value that maximizes the Integrated Classification Likelihood (ICL) (see Biernacki et al., 2000). The SMB results show that the optimal number of clusters in the full network is 35. The maximum tags by cluster are 40, while the minimum is 4. The clusters and a block model representation are shown in Appendix 2. Each cluster is named using the two nodes with the highest degree centrality that belongs to the cluster(except when there is only one node). The clusters are used in the full network visualization in Fig. 4.

Second, following Borgatti et al. (2013, p. 90) we constructed a new network where technology clusters are aggregated nodes and the ties represent the relations between these 35 higher-level technology clusters. This allows for calculating centrality measures that indicate the relative importance of technology clusters within the digital transformation. Using the relatedness as weights, we calculated weighted measures of closeness and betweenness centrality (using the package *tnet* in R, see Opsahl et al., 2010). To calculate these measures, we used an alpha value of 1.5, such that the strength of the ties (i.e. the volume of a connection) carries more weight than the path length between nodes (i.e. the length of the connection). This choice follows from the reasoning that the quantity of start-ups that bridge technologies is more important than the question of whether there is a single start-up that does so. A radial measure[3] like closeness centrality calculates how relatively easy it is to reach all the other nodes in the network from a focal node. A node's higher closeness value indicates a higher connectivity/level of outreach within the network. Nodes that perform a transmission role to particular network sectors tend to score higher on this indicator. By contrast, a medial measure[3] such as betweenness centrality indicates how often a specific node is on the shortest route between other nodes (Borgatti and Everett, 2006). In a large complex network such as our technology space, a great proportion of nodes in the network receives a betweenness value close to 0 because of they do not often lie in the shortest path between other nodes. Thus, nodes with a higher betweenness value can be seen as the most dominant technologies in the whole structure. Therefore, if there are several nodes with a high betweenness centrality, the network is of a 'polycentric galaxy type' rather than a 'monocentric star type'.

## Mapping the digital transformation in knowledge-intensive services

*Capturing the digital transformation in knowledge-intensive services over time*

Before we present our technology space analysis of the current moment of digital transformation, it is important to establish that such a transformative development of recombinant innovation and sector coalescence is indeed taking place. To capture this longitudinal perspective, we subdivided the dataset by the founding year for each company and built three different cumulative networks. The first network only shows companies established in the 1990s, the second

**Table 1**
Summary of networks.

| | Network | | | |
|---|---|---|---|---|
| | Full | Time 1 | Time 2 | Time 3 |
| Years | 1990–2020 | 1990–2000 | 1990–2010 | 1990–2020 |
| Start-ups and Scale-ups [a] | 40,754 | 4538 | 12,318 | 36,695 |
| Tags (Nodes) | 694 | 500 | 642 | 657 |
| Relationships (Edges) [b] | 17,237 | 5208 | 10,454 | 14,922 |

Notes. (a) 4059 companies did not have information about the founding year. (b) Only significant ties after backbone extraction (see Section 4.3.1).

[3] Radial centrality measures assess walks through the network that emanate from or terminate at a given node directed by an algorithm, they are therefore 'localized' within the network. Medial measures measure the amount of walks that walk through a node directed by an algorithm, they are therefore 'global' (Borgatti & Everett, 2006).

network adds the 2000s and the third network the 2010s (see Table 1). We built the technology space for each subgraph, shown in Fig. 3. The succession of technology space networks shows how more recently incorporated firms use different technological combinations than their older counterparts.

To demonstrate the digital transformation between these three networks, following the selection of Balland and Boschma (2021), we highlighted 10 key technologies they label as 'IT4s'[4] in these technological spaces: (1) 3D Technology; (2) Artificial Intelligence; (3) augmented reality; (4) robotic; (5) autonomous vehicles; (6) cloud computing; (7) cybersecurity; (8) machine tools; (9) quantum technologies; and (10) integration systems. By tracing these major technologies, a picture of the digital transformation of knowledge-intensive services through time is obtained.

In Fig. 3, the 10 IT4s are seen to gradually come together in the network's centre, when newer start-ups are compared to older ones, evidencing technological convergence (Teece, 2018). The size of the nodes/labels reveals the occurrence of the tags within the companies at each time point, through which is possible to appreciate how the 10 I4Ts have had significant changes in their incidence through time. Artificial Intelligence, 3D technology, cybersecurity and augmented reality are notably more present with newer firms, and it suggests that artificial intelligence is the central focus of the newest generation of start-ups (Agrawal et al., 2019). Balland and Boschma (2021)'s analysis of the relatedness between the 10 IT4s in European regions (idem, p. 1656) based on patent data reveal important similarities to the 1990–2020 technology space shown in Fig. 3 that utilizes near real-time data. Our findings converge with Balland and Boschma (2021)'s where AI moves to the centre of the network, additive manufacturing is closer to augmented reality; cybersecurity, cloud computing and integration systems are more closely related, as well as autonomous vehicles, autonomous robots and machine tools. Quantum technologies is still more disconnected to other technologies except AI. This convergence of findings gives confidence in the validity for our near real-time dataset to measure technological change on this coarser level of analysis. The near real-time data additionally allows a deeper exploration of how technologies relate to each other in the present moment.

### *The structure of the main network*

Fig. 4 shows a detailed technology space of the digital transformation in the backbone of the knowledge-intensive services (see Section 4.3.1). The nodes in Fig. 4 represent the tags, and their size indicates their relative frequency in the dataset. The square boxes around groups of nodes are the 'technology clusters' derived from the SBM estimation. The technology clusters' hyphenated names are the compound of its two most prominent tags. For instance, we can observe that the tags around Financial Services, Blockchain and Cryptocurrency together form a technology cluster named *FinTech - Cryptocurrency*. The edges correspond to non-random technological connections and are plotted through the force-directed drawing algorithm so that strongly connected tags are more closely located to each other.

Fig. 4 also shows where the different technology clusters intermingle and overlap, indicating where convergence or integration of technology is likely to happen. The network reveals in detail the technologies that the World Economic Forum (2018) identified as pivotal to the digital transformation: 'Artificial Intelligence' (the *Machine Learning - Artificial Intelligence* cluster), 'Big Data Analytics and Cloud' (in the overlap between the *Machine Learning - Artificial Intelligence* and *Software - Cloud Technology* clusters), 'Custom Manufacturing and 3D printing' (in the overlap between *Monitoring - 3D printing* and *Hardware - Industrial Technology*), 'Internet of Things (IoT) and Connected Devices' (in the overlap between *Internet of Things – Telecommunications* and *Computer Vision - Sensor*), 'Robots and Drones' (in the overlap between *Computer vision - Sensor* and *Internet of Things - Telecommunications*) and 'Social Media and Platforms' (the overlap between *Social - AdTech, Navigation - Search Engine* and *Mobile - Media*). The last, 'Autonomous Vehicles' is subsumed in the *Hardware - Industrial Technology* cluster. This low prominence is a likely result of our knowledge-intensive service focus.

A key analytical inference drawn from Fig. 4 relates to notions of 'proximity' and 'distance' in the visualization. Tags and their corresponding technology cluster that are proximate to one another are more strongly related (evidencing potential sector coalescence and technological convergence). This strong relatedness is apparent in the overlap of technology cluster boxes, for instance, at the *Gaming - Console - PC Gaming* and *Content Production - Virtual Reality* clusters. Alternatively, *FinTech - Cryptocurrency* and *Health - Medical Devices* are remote from one another due to their unrelatedness. That does not mean there are no companies specialized in the interface, but they are a rare breed.

When examining Fig. 4, it is apparent that some technology clusters are much more coherent and 'compact' than others. Overall, the relationships between clusters are significant representations of the intensity of cross-fertilization between different technologies. We can already observe that, at least from a knowledge-intensive services perspective, some technologies (e.g., Internet of Things - Telecommunications) are more central to the digital transformation than others (e.g., Computer Vision - Sensor or Social - AdTech). Therefore, to understand the main components of the digital transformation in the knowledge-intensive services, we will use density and centrality measure to delve further into the technology space's structure.

### *Centrality of technologies: roles in the digital transformation*

The SBM clustering not only demarcates the main tag clusters in the network, but it also provides additional indications about the technology clusters' overlaps. The SMB allows calculating a density measure that quantifies how many ties are shared between and within clusters (see Appendix 2 for a blockmodel representation of the clusters using the density). By averaging the density values per technology cluster, we obtain a pervasiveness indicator of each technology cluster. The higher this value, the more strongly this technology cluster is connected to all the other clusters. The *Navigation - Search Engine, Enterprise Software - Information Technology*, and *Deep Tech - Recognition Technology* technology-clusters present the highest scores. A closer look at these specific technology clusters reveals that they contain relatively generic tags that one can easily imagine to be relevant to every sector. Nevertheless, although these technology clusters are the most likely to connect to other technologies, they are not necessarily the most central in the network. To grasp this other dimension, we calculated the average closeness centrality and betweenness centrality for each technology cluster (see Section 4.3.2).

Fig. 5 plots our three digital transformation indicators for the knowledge-intensive services technology space. Pervasiveness (a cluster's Average Density) is depicted on the Y-axis, Connectivity (a cluster's Average Closeness Centrality) on the X-axis, and Centricity (Betweenness Centrality) is visualized by node colour, Fig. 5 shows that nodes with the highest betweenness centrality values correlate with high values of the other dimensions. However, the correlation between pervasiveness and connectivity, is only moderate ($r = 0.45$, $p < 0.01$). These differences require a careful discussion about the different dynamics within the digital transformation.

To understand the roles of specific technology clusters, we applied the distinctive terminology introduced by the European Patent Office (Ménière et al., 2017) to study Industry 4.0 and which distinguishes 'core technologies', 'enabling technologies', and 'application domains'. This taxonomy is increasingly adopted in academic research (Capello and Lenzi, 2021). Our specific designation of roles will differ from Industry 4.0 research as we focus on knowledge-intensive services and not

[4] We preserve Dealroom.co tags names rather than utilizing Balland and Boschma (2021, p. 1654)'s exact terms.

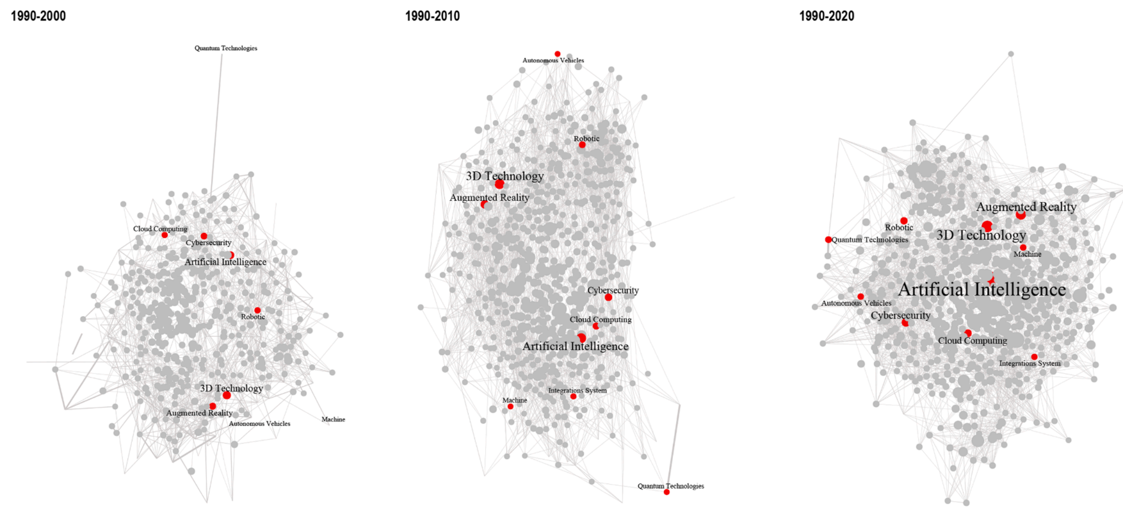


**Fig. 3.** The digital transformation of start-ups technology space from 1990 – 2020. Note: Size of the nodes represents occurrence. Width of the edge represents strength of the relationship. Industry 4.0 technologies (I4T) have been identified throughout the years (nodes in red, see Balland and Boschma, 2021).

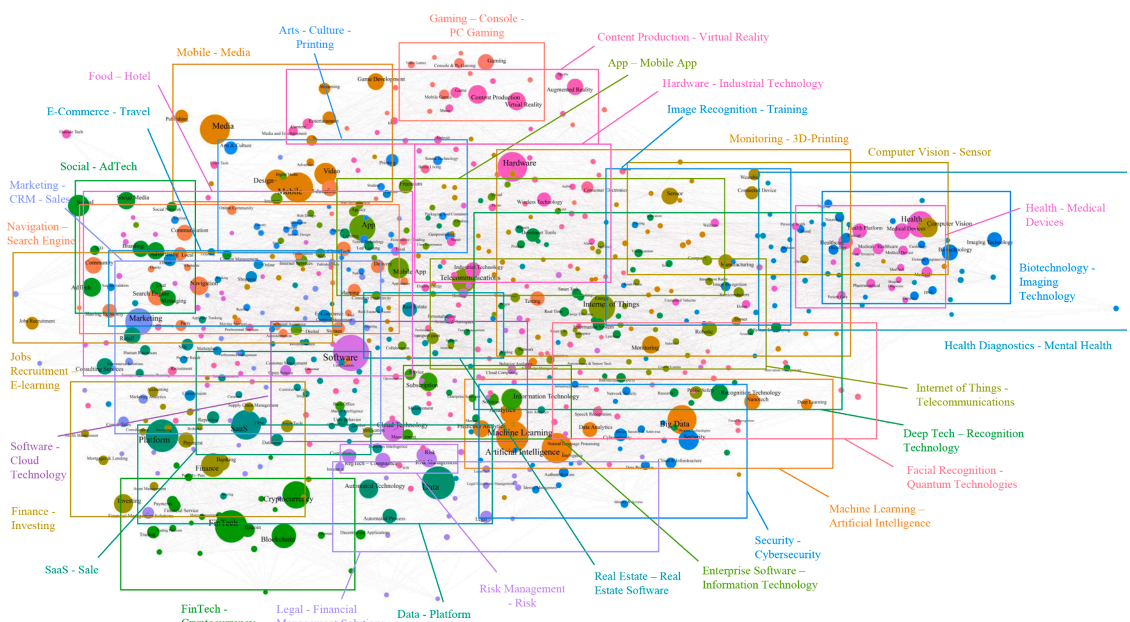


**Fig. 4.** Technology space of the knowledge-intensive services sector. Note: Size of the nodes represents occurrence. Width of the edge represents strength of the relationship. Clusters derived from the SBM are highlighted with colours and squares. The names of the clusters represent the two most important nodes within each cluster.

on industrial sectors. If we examine the top right corner of Fig. 5, we note that several technology clusters with the highest average betweenness centrality (centricity) are indeed technologies that are often considered central to the digital transformation (Agrawal et al., 2019). Specifically, we refer to *Machine learning - Artificial Intelligence, Data - Platform* and *DeepTech - Recognition Technology* and will label these 'core technology clusters'. There are also technology clusters in the top right corner that are pervasive and connective, yet they are less likely to be in the centre of the digital transformation, given their low centricity value. Examples are *Enterprise Software - Information Technology, Hardware - Industrial Technology, App - Mobile App*. We could say that these are also more 'generic categories' that are not exclusively associated with the digital transformation but are relevant to many sectors. Note that our findings concur with Vial (2019) that *FinTech - Cryptocurrency*, which often features in discourses on the digital transformation, is not really pervasive. It is primarily relevant to the digital transformation of the financial sector but not so much elsewhere in the knowledge-intensive services, which explains its relative high connectivity compared to its lower centricity and pervasiveness scores.

On the other side of Fig. 5, in the bottom left corner, we mostly find what we could call 'application domains' of the digital transformation with technology clusters such as *Food - Hotel, Real Estate - Real Estate Software, Gaming - Console - PC Gaming, Legal - Financial Management Solutions*, and *Health Diagnostics - Mental Health*. Note that these sectors are not irrelevant to the digital transformation, they in fact, tend to represent those 'blue chip' sectors that the World Economic Forum (2018) predicts will be severely impacted by the digital transformation.

However, it seems unlikely that the transformation of blue chip sectors will be through a direct link to the core technology clusters, as these tend to be quite remote from the application domains within the technology space (cf. Balland et al., 2021). A technology space perspective allows zooming in and analyse the 'enabling technology

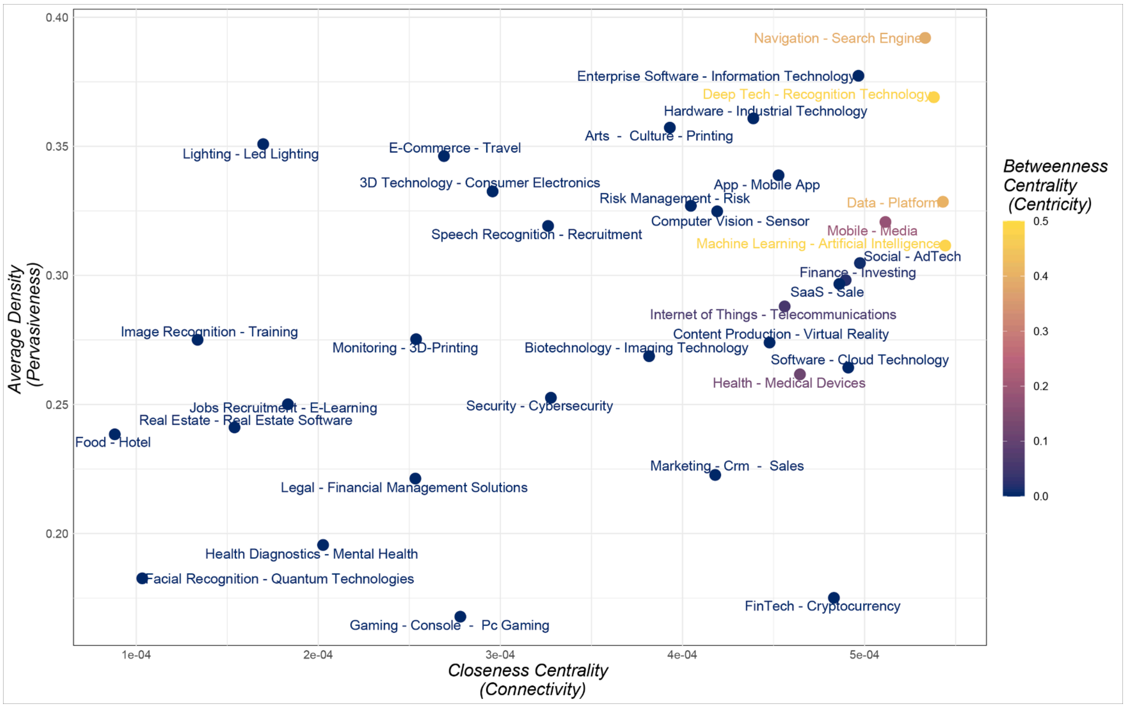


**Fig. 5.** The centrality of technology clusters: Pervasiveness (average density), connectivity (average closeness centrality) and centricity (average betweenness centrality).

clusters' that build bridges. Here we are particularly interested in technology clusters that have a relatively higher score on the connectivity dimension than on the centricity and pervasiveness dimensions and might provide connections to the blue chip application domains. As a technology cluster scores a relatively high connectivity (closeness centrality), one explanation is that it is likely to be a bridge to otherwise

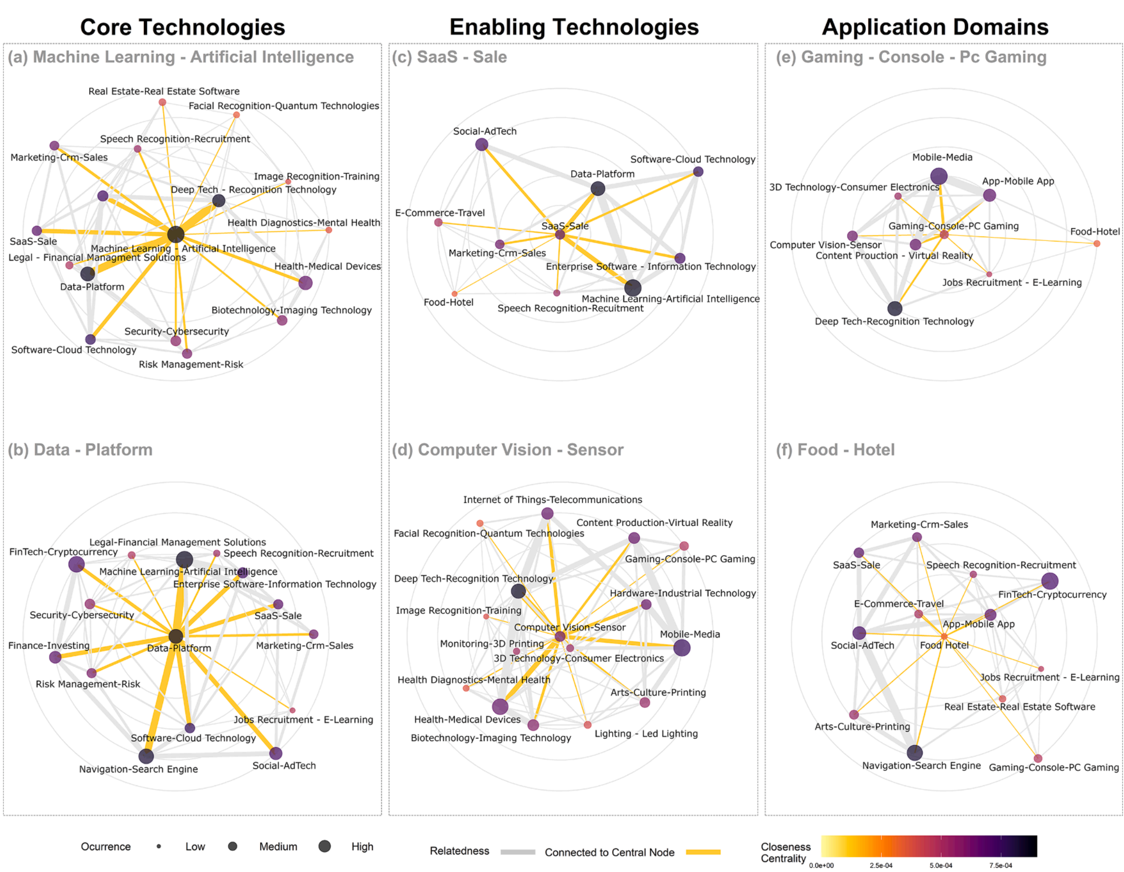


**Fig. 6.** Selected Ego networks of technology clusters.

weakly connected areas of the network. Here technology clusters such as *Software as a Service (SaaS) - Sales, Internet of things - Telecommunications*, and *Content Production - Virtual Reality* stand out as candidates. Going back to Fig. 3, visual inspection confirms that these sectors occupy an intermediate position between the most central technology clusters and the blue chip application domains.

*A closer look at types of technology clusters*

Based on the above dissection of the technology space, we can further focus on these three distinct idealized 'roles' of 'core technologies', 'enabling technologies' and 'application domains' (Ménière et al., 2017) that technology clusters play in the digital transformation. 'Core technology clusters' will score high on pervasiveness, centricity and connectivity, and drive the digital transformation. Conversely, the 'application domain technology clusters' tend to score low on all three indicators, denoting sectors that are subject to the digital transformation but not necessarily driving technological change. Thirdly, the 'enabling technology clusters' play a significant role by being instrumental connectors between core technologies to application domains in the wider knowledge space. These are clusters that have a relatively high score on the connectivity measure and tend to occupy a bridging position in the force-directed visualization of the network.

To investigate the different types of roles, we chose 2 technology clusters for each of the categories: 'core technologies', 'enabling technologies', and 'application domains' and delve deeper in this idealized typology by looking at simplified ego networks (Fig. 6). Ego networks show the 'immediate neighbourhood' of a focal technology cluster and the direct connections it has to other technology clusters. This allows us to get a sense of the opportunities and constraints a specific technology cluster faces (Hanneman and Riddle, 2011) in getting access to the technology clusters central to the digital transformation. The edge thickness represents weights, i.e., the frequency of the connections. Direct edges are indicated in orange, indirect edges (where ego can be 'bypassed') are in grey.

Fig. 6a (*Machine Learning - Artificial Intelligence*) and Fig. 6b (*Data - Platform*) show the ego networks of two core technology clusters. Perhaps unsurprising but nevertheless important is that the strongest connections between these core technology clusters are with other core technology clusters. The consecutive high betweenness nodes '*Navigation - Search Engine, Data - Platform, Machine Learning - Artificial Intelligence, Deep Tech - Recognition Technology*' seem to form a kind of 'beaded string' backbone structure that gives the polycentric network its main form. The core technologies do only in a very limited extent relate directly to the application technology clusters. In Fig. 6e, the *Gaming - Console - PC Gaming* technology cluster only has a relatively weak direct connection to *Deep Tech - Recognition Technology*, Fig. 6f (*Food - Hotel*) only has a connection to high-betweenness technology cluster *Navigation - Search Engine*, which is so pervasive that we can cast doubt how core that technology cluster really is to the digital transformation.

This brief examination of two core and two application domain technology clusters, supports the argument that enabling technology clusters do indeed exist and are likely to play an important part in the diffusion of the digital transformation to the more mundane sectors of the economy. To explore this notion further, we selected two nodes that fit the description of enabling technology cluster and that also visually in Fig. 6 seem to have a bridge position in the spacing of the network. These enabling technology clusters are *SaaS - Sale* (Fig. 6c) and *Computer Vision - Sensor* (Fig. 6d) Fig. 6c visually confirms the character of the enabling technology cluster. It has relatively strong connections to the core technology clusters *Data - Platform* and *Machine Learning - Artificial Intelligence* while also having salient linkages to application domain clusters *Food - Hotel* and E-*Commerce - Travel.* This analysis suggests a likelihood that these sectors will come into contact with the digital transformation delivered through the Software as a Service infrastructure.

Fig. 6d, shows a slightly more complicated picture because *Computer Vision - Sensor* is an example of an enabling technology cluster that scores higher on the pervasiveness (Average Density) measure. It only has a strong direct connection to the core technology cluster *Deep Tech - Recognition Technology.* However, it is connected to several other enabling technology clusters such as *Internet of Things - Telecommunications* and *Content Production - Virtual Reality. Computer Vision - Sensor* is also intertwined with other high pervasiveness technology clusters such as *Mobile - Media and Hardware - Industrial Technology*. These relations together explain the relatively high pervasiveness of *Computer Vision - Sensor*. Nevertheless, the reason to still include the technology cluster in our examples of enabling technology clusters is because it clearly unlocks the medical and HealthTech applications to the digital transformation. The clear and otherwise somewhat isolated connections to *Health Diagnostics - Mental Health, Health - Medical Devices* and *Biotechnology - Image Technology* illustrate *Computer Vision - Sensor*'s bridging role. As healthcare is one of the major economic sectors predicted to be transformed by the digital transformation (World Economic Forum, 2018), the fact that it is only indirectly connected to the technologies driving that transformation is important. It indeed puts the spotlight on a need to investigate enabling technologies in-depth in future research.

## Conclusion

This paper contributes to the extant debate on digital transformation that has become a key pillar of contemporary industrial and technological change. This paper sought to enrich theoretical and empirical understanding of the digital transformation. Theoretically, building on Perez (2010), we made the case that the current digital transformation ought to be seen as a new episode, a new technological paradigm, in a longer ongoing fifth technological revolution centred around the ICT General Purpose Technology that started in the second half of the 20th century. We then addressed the empirical underspecification in accounts of the digital transformation through a novel technology space analysis on near real-time data. The technology space analysis generated a detailed map of the digital transformation in knowledge-intensive services, examining how technologies and clusters relate to each other and converge. Furthermore, our paper makes three main contributions to the academic literature on evolutionary technological change.

First, we have unpacked the digital transformation by developing new data-driven, near real-time, methods to inductively build technology spaces of the knowledge-intensive services. This opens up new avenues of research within the established technology space research agenda (Hidalgo, 2021; Whittle and Kogler, 2019), which has so far largely relied on statistics with imposed taxonomies of technology categories, particularly patent data statistics. Such imposed taxonomies have significant drawbacks when studying fast-moving and transformative innovation. Real-time data of innovative tech companies overcome the arguably more substantive limitations associated with patent data, not least including the long lag between patent application filing, granting and industry usage, and the bias in patent data towards the innovations of large corporations.

Second, we have developed new insights that conceptualize the differential roles within a polycentric technology space by embedding our findings in Ménière et al.'s (2017) taxonomy of 'core', 'enabling', and 'application domain' technologies. We inductively determined the core technology clusters at the innovation frontier and the enabling technology clusters that play a key role in the transmitting the digital transformation to the application domains across the knowledge-intensive services.

Third, combining technology space analysis with near real-time data provides a more finely grained and potentially dynamic perspective on economic transformation. Heeding Allen's (1994) advice, using a two-phase modelling of technology categories allows a fluid and dynamic definition of technologies. This lays the groundwork to be able to map sector coalescence and the changing identity and composition of industries and technology in real-time.

While the focus of this paper is the digital transformation of knowledge-intensive services, the approach used can be employed across other sectors in mapping technology spaces. Indeed, there is a considerable opportunity to apply the near real-time datasets to analyse the technology spaces in different sectors and across different places. The used methodology enables studying the coherence of technology clusters and quantify the overlap between them, thereby eliciting new insights on how sectors and technologies relate. Using social network analysis metrics makes it possible to quantify characteristics of the structure and properties of the main actors in a technology space. This approach therefore beholds considerable opportunities for foresight and futures research on innovation and technological recombination.

Finally, the paper also beholds implications for businesses, policy makers, and other industry stakeholders, such as venture capital firms. In exploring the knowledge-intensive services sector's technology space, our research emphasises the importance of extending the understanding of the co-evolution with other sectors. For instance, it becomes possible to monitor how the cross-fertilization between established industry categories redefine themselves to inform debates on servitization and platformization in different application domains and/or different locations. This provides an important focus for policy interventions to target and support the future competitiveness of current and emergent industries and technologies (Frenken et al., 2012). For businesses, our analysis can provide a better self-understanding of the position within the technology spaces they are part of and which missing links they might want to consider engaging with, tapping into complementary knowledge and or engage in new markets.

Overall, the study reflects on the nature of the digital transformation phenomenon by rethinking the role that different technologies play. While focusing not only on those at the centre of the transformation but also on those technologies that bring the innovation to the more mundane application domains, overlooked dynamics of technological change come into view. Key enabling technologies have a crucial and instrumental role in connecting core technologies to application domains. Beyond reinforcing the core technologies, we propose to switch the attention to these technological bridges to trace how new or significantly improved products or processes emerge from seemingly unrelated corners of the economy.

## Author statement

Michiel van Meeteren: Conceptualization, Methodology, Writing - Original Draft, Writing - Review & Editing, Supervision

Francisco Trincado-Munoz: Methodology, Software, Formal analysis, Data Curation, Writing - Original Draft, Visualization

Tzameret H. Rubin: Writing - Review & Editing, Resources

Tim Vorley: Writing - Review & Editing, Funding acquisition, Principal Investigator

## Appendix 1. To select the start-ups and scaleups from Dealroom.co that fall within the remit of knowledge-intensive services, we conducted the following steps

*Step 1*. We reviewed the available filter criteria at Dealroom.co. Advanced filters in Dealroom.co include business model type, income streams, industry, sub-industry, and technologies (for more information, see https://knowledge.dealroom.co/knowledge/using-filters). We decided in principle to use only industry filters.

*Step 2*. From the available industry filters, we selected those unambiguously referred to knowledge-intensive services from the industry filters (i.e., Enterprise Software, Fintech, Health, Jobs Recruitment, Legal, Marketing, Media, Real Estate, Security and Telecom).

*Step 3*. To cross-check and expand our selection criteria, we validate the chosen filters using a random 1000 knowledge-intensive companies of the financial and insurance sectors obtained from Van Meeteren et al. (2020)'s study. By finding the same companies in Dealroom.co, we checked the coverage of the filters. As a result, we added Gaming and Hosting as part of our industry selection filters because these turned out fully interwoven with other knowledge-intensive services.

*Step 4*. Finally, we decided to include companies into the dataset that will mention one application industry and one technology filter. The final selection filters are highlighted in bold in Table 2. Industry Application includes all available 27 filters.

**Table 2**
Dealroom.co's industry and technology filters.

| |
|---|
| Industry Application |
| Dating, Education, Energy, **Enterprise software,** Event tech, Fashion, **Fintech,** Food, **Gaming, Health,** Home living, **Hosting, Jobs recruitment,** Kids, **Legal, Marketing, Media,** Music, **Real estate,** Robotics, **Security,** Semiconductors, Sports, **Telecom,** Transportation, Travel, Wellness beauty |
| Technology Application |
| 3D Technology, Artificial Intelligence, Autonomous and Sensor Tech, Big Data, Blockchain, Computer Vision, Connected Device, Deep Learning, Deep Tech, Hardware, Internet of Things, Machine Learning, Mobile App, Natural Language Processing, Quantum Technologies, Recognition Technology, Virtual Reality |

Note: Chosen filters to construct the dataset are highlighted in bold.

## Appendix 2. Clusters obtained through Stochastic Blockmodel, Number of Tags and Tags for each Cluster

As result of the blockmodel clustering, we obtain 35 clusters of categories (see Table below). Fig. 7shows the partition of clusters and the relationship between clusters in a heatmap (Storme et al., 2019). The density value is used to account for the number of existing ties within and between clusters respect to the possible number of ties (Faust and Wasserman, 1992). The colours are an indication of the density value. As the blockmodel representation is a symmetric matrix, the diagonal shows the 'internal density' of each cluster. Density values closer to one (i.e., red colour) are indication of high internal consistency amongst tags in the cluster; while values closer to zero (i.e., yellow colour), represent less coherent clusters.

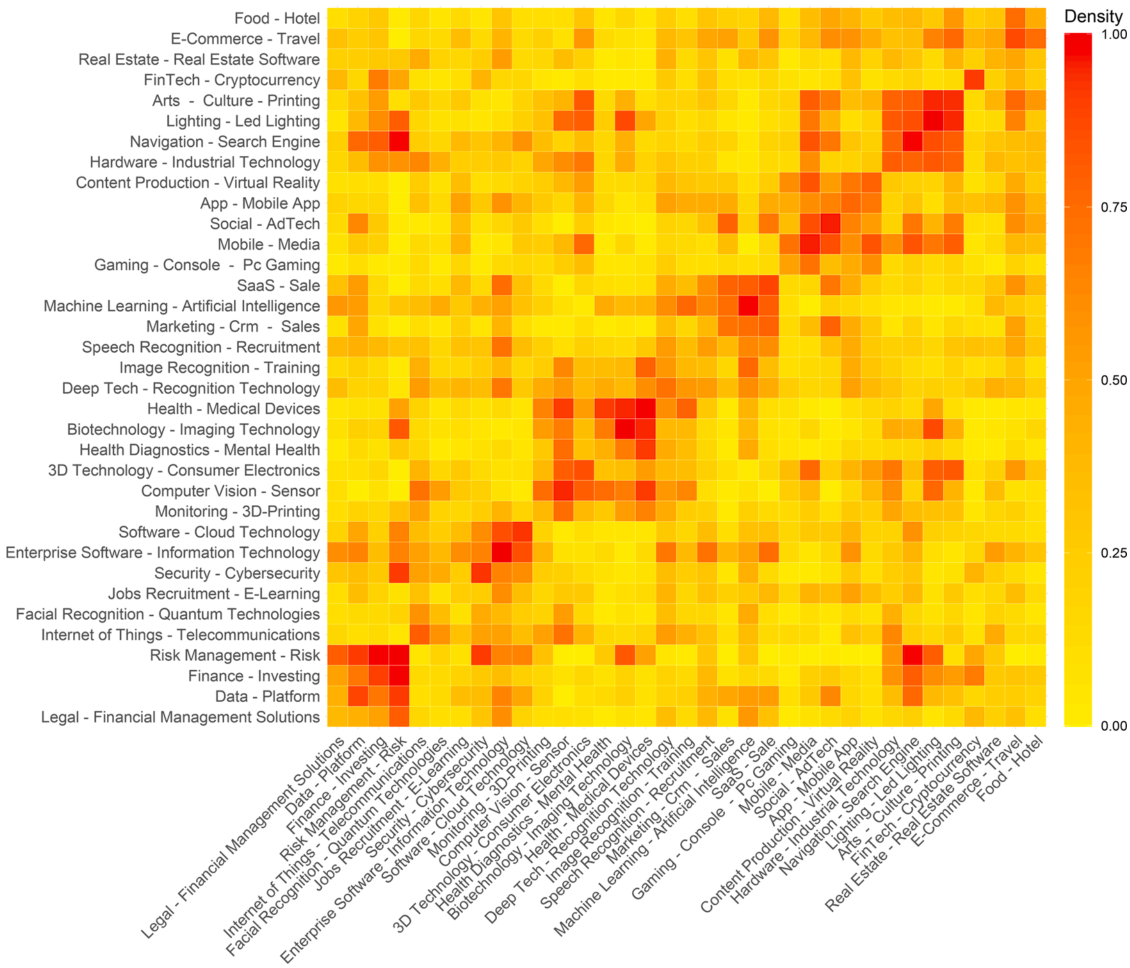


**Fig. 7.** Cluster heatmap.

| Cluster | Cluster Name | N Tags | Tags |
|---|---|---|---|
| 1 | 3D Technology - Consumer Electronics | 13 | 3D Technology, Consumer Electronics, Home Living, Ecommerce / Trading, Fitness, Eye Care, Smartphone, Eyewear, Consumer Goods, Children, Lifestyle, Smart Watch, Smart Device |
| 2 | App - Mobile App | 26 | App, Mobile App, Freemium, Internet Services, Internet, Digital, Agency, Web, Network, Consumer Productivity, Collaboration, Creating, Virtual, Web Development, Digital Media, Web Design, User Experience, Users, World, Interactive, Location Based, Production, Event Management, Experience, Free, Sharing |
| 3 | Arts & Culture - Printing | 24 | Arts & Culture, Printing, Geopositioning, Sound Technology, Green Technology, Student, Tourism, Packaging and Containers, Renting, Luxury, Apparel, Interior Design, Furniture, Decoration, Parking, Cleaning Services, Cleaning, Clothes, Ride Sharing, Ride, Shoes, Tea, Truck, Speaker |
| 4 | Biotechnology - Imaging Technology | 14 | Biotechnology, Imaging Technology, Cancer, Oncology, Neurology, Genetics, DNA, Genome Engineering, Surgery, Blood, Cardiology, Diabetes, Stroke, Drug |
| 5 | Computer Vision - Sensor | 7 | Computer Vision, Sensor, Manufacturing, Connected Device, Wearable, Drones, Device |
| 6 | Content Production - Virtual Reality | 25 | Content Production, Virtual Reality, Augmented Reality, Game, Content, Media and Entertainment, Music, Android, Event Tech, Sports, IoS, Photo, 21st Century Skills, Audio, Gamification, Sport, Kids, Broadcast, Creative Solutions, Live, Animation, Reality, Iphone, Graphic Design, Tablet |
| 7 | Data - Platform | 14 | Data, Platform, Automated Technology, Retail, Consulting Services, Automated Process, Reporting, Database, User behaviour, Human Resources, Enterprise Resource Planning, Applicant Tracking, Scoring, Onboarding |
| 8 | Deep Tech - Recognition Technology | 33 | Deep Tech, Recognition Technology, Developer Tools, Information System, Tech, System Engineering, Intellectual Property, Smart Tech, Real Time, Research, Visualization, Learning, Product, Market, Tracking, Tool, Support, Innovation Management, Building, People, Innovation, Scientific, Time Management, Process Technologies, Algorithm, Help, Patenting, Based, Intelligent Systems, Quality, Modelling, Power, Efficiency |
| 9 | E-Commerce - Travel | 14 | E-Commerce, Travel, Shopping, Commission, Online, Marketplace, Fashion, Pay Per Result, Accommodation, Ticketing, Performance Management, Booking, Deal Comparison, Merchant Tools |
| 10 | Enterprise Software - Information Technology | 8 | Enterprise Software, Information Technology, Subscription, Solution, Service, Management, Back Office, Enterprise Solutions |
| 11 | Facial Recognition - Quantum Technologies | 22 | Facial Recognition, Quantum Technologies, Industrial Automation, Quantum Computing, Industrial - IoT, Predictive Maintenance, Autonomous Vehicles, Surveillance, Edge Processing, Satellite Tech, Face Recognition, Fleet Management, Clean Energy, Network Hardware, Smart Building, Military, Automotive Cybersecurity, Vehicle, Telematics, Space Tech, Iiot, Intrusion Detection |
| 12 | Finance - Investing | 21 | |

(continued on next page)

(*continued*)

| | | | |
|---|---|---|---|
| | | | Finance, Investing, Banking, Payment, InsurTech, Verification, Accounting, Supply Chain Management, Mortgages & Lending, Asset Management, Wealth Management, Invoicing, Crowdfunding, Credit, Brokerage, Debt Collection, Audit, Due Diligence, Cannabis, Retirement, Treasury |
| 13 | FinTech - Cryptocurrency | 23 | FinTech, Cryptocurrency, Blockchain, Bitcoin, Trading, Financial Service, Payments, Peer-To-Peer, Ethereum, Trading Platform, Money Management, Decentralised Applications, Wallet, Personal Finance, Exchange, Currency, Financial Exchanges, Smart Contracts, Money Transfer, Transaction, Foreign Exchange, Card, Token |
| 14 | Food - Hotel | 24 | Food, Hotel, Freelancers, Travel and Tourism, Farming, Betting & Gambling, Online Travel Agency, Job, Search, Buy & Rent, Price Comparison, Jobs / Recruitment, Sell, Buy, Pricing, PR, Booking & Search, In-Store Retail & Restaurant Tech, Restaurant, Directory, Classifieds, Public Relations, Food And Beverage, Coupons, Leisure |
| 15 | Gaming - Console & Pc Gaming | 19 | Gaming, Console & Pc Gaming, Mobile Games, Video Games, Digital Entertainment, VR-Experiences, Sport Platform & Application, Studio, Film Production, Video Chat, PC Gaming, Immersive Technologies, Video Streaming, Esports, Play, Esport, Digital Signs, Friends, EdTech |
| 16 | Hardware - Industrial Technology | 16 | Hardware, Industrial Technology, Wireless Technology, Aviation & Aerospace, Outside Tech, Water, Home, Electric Energy, Unmanned Vehicles, Alarm, Electronic, Solar Energy, Oil & Gas, Environment, Recycling, Waste Reduction |
| 17 | Health - Medical Devices | 20 | Health, Medical Devices, Health Platform, Healthcare, Medical / Healthcare, Medical, Medical Device, Pharmaceutical, Non-Invasive, Wellness, Patient Care, Personal Health, MedTech, Diagnostic, Hospital, Digital Healthcare, Care, Clinical, Doctor, Treatment |
| 18 | Health Diagnostics - Mental Health | 24 | Health Diagnostics, Mental Health, Telemedicine, Home Maintenance, Life Science, Radiology, Rehabilitation, HealthTech, Disease, Digital Health, Therapeutics, Medical Imaging, Bioinformatics, orthopaedic, Hearing, Dental Care, Therapy, Femtech, Nutrition, Brain, Early Detection, Prevention, Sleeping, Biomedical |
| 19 | Image Recognition - Training | 17 | Image Recognition, Training, EIC, Assistance, Cognitive, Neuroscience, Human Computer Interaction, Image, Scanner, Decision Making, Real, Emergency, Speech, Start-Up, Psychology, Life, Alert System |
| 20 | Internet of Things - Telecommunications | 29 | Internet of Things, Telecommunications, Robotic, Public Safety, Transportation, Energy, Semiconductors, Computer, Construction, Automotive, Innovation Radar, Autonomous & Sensor Tech, Smart City, AgriTech, Industry 4.0, Mobility, Aerospace, Industrial, Smart Home, Energy Efficiency, Control Systems, Connectivity, Engineering Services, Homeland Security, Camera, Safety, defence, Machine to Machine, Space |
| 21 | Jobs Recruitment - E-Learning | 40 | Jobs Recruitment, E-Learning, Workspace, Communications Infrastructure, Outsourcing, Voice Recognition, App Development, Architecture, VOIP, Productivity Tools, Project Management, Location Analytics, Wifi, Phone, Distribution, Online Learning, Productivity Software, Project, Integrations System, Team Collaboration, Work, FT 1000, Custom, Mobile Technologies, Programming, Broadband, Translation, IServices, Cross Platform, Scheduling, Coding, Television, Mobile Device, Product Development, Virtual Assistant, Meeting Management, Display, Radio, Mobile Development |
| 22 | Legal - Financial Management Solutions | 28 | Legal, Financial Management Solutions, Insurance, LegalTech, Legal Documents Management, Fraud Management, Alternative Data, Billing, Law Enforcement, Legal Information, Contract Management, Business Analytics, Information Services, Self-Service and Lawyer Marketplace, Financial Management, Anti Money Laundering, RPA, Loan, International, Inventory Management, Fraud Detection, Retail Tech, Credit Scoring, Fund Management, Anti Fraud, Mining Technologies, Saving, See Cost Management |
| 23 | Lighting - Led Lighting | 8 | Lighting, Led Lighting, Women, Heating, Lenses, Cooling Tech, Dietary Supplements, Superfood |
| 24 | Machine Learning - Artificial Intelligence | 12 | Machine Learning, Artificial Intelligence, Big Data, Analytics, Predictive Analytics, Nanotech, Data Analytics, Deep Learning, Natural Language Processing, Intelligence, behaviour Analytics, Artificial, |
| 25 | Marketing - CRM & Sales | 24 | Marketing, CRM & Sales, Marketing Analytics, Ecommerce Solutions, Campaign Management, Publisher Tools, Targeting, Monetization, Influencer Marketing, Mobile Advertising, Loyalty Program, Sales Analytics, Digital Marketing, E-Mail Marketing, Audience, Facebook, Omnichannel, Matchmaking, Video Content, Retargeting, Online Marketing, Conversion, Content Discovery, Mobile Marketing |
| 26 | Mobile - Media | 10 | Mobile, Media, Design, Video, Game Development, Entertainment, Publishing, Streaming, Tv, Adventure |
| 27 | Monitoring - 3D-Printing | 25 | Monitoring, 3D-Printing, Semiconductor, Elder Care, Sustainable Development Goals, Simulation, Detection, Laboratories, Optical Technology, Embedding Technology, Research and Development, Material, Motion, Remote, Direct-To-Consumer, Mechanical Solutions, Cad, Innovation Procurements, Wellness / Beauty, Equipment, Designers, Used, Chemical, Laser Technology, Core Sustainable Impact |
| 28 | Navigation - Search Engine | 25 | Navigation, Search Engine, Community, Education, Communication, Testing, CleanTech, Sharing Economy, Delivery, Local, Mapping, Storage, Party, On-Demand, Online Community, Administration, Certification, Technical Assistance, Presentation, Moving Services, Appliances, Wholesale, Fuel, Charity, Debate |
| 29 | Real Estate - Real Estate Software | 22 | Real Estate, Real Estate Software, Navigation & Mapping, Travel Analytics & Software, PropTech, Real Estate Services, Logistic, Sustainability, Logistics & Delivery, Ediscovery, Car, Public Sector, Property, Airplanes, Private, Property Management, Office Space, Traffic, Indoor Navigation, City, Commercial Real Estate, Workspaces |
| 30 | Risk Management - Risk | 4 | Risk Management, Risk, Compliance, RegTech - Compliance |
| 31 | SaaS - Sale | 19 | SaaS, Sale, Measurement, Business Intelligence, Personalisation, Chatbot, Customer Management, CRM, Market Intelligence, Text Analytics, Lead Generation, Customer Service, Insight, Customer, Recommendation, Email, Semantic, Engagement, Review |
| 32 | Security - Cybersecurity | 19 | Security, Cybersecurity, Cloud & Infrastructure, Authentication, Data Protection, Network Security, Identity & Access, Device Security & Antivirus, Identity Management, Infrastructure Services, Governance, Protection, Privacy Protection, Secure, Encryption, Threat Intelligence, Mobile Security, Cryptography, GDPR |
| 33 | Social - AdTech | 10 | Social, AdTech, Social Media, Advertising, Branding, Messaging, Chat, Social Network, SEO, Content Management |
| 34 | Software - Cloud Technology | 17 | Software, Cloud Technology, Open Source, Hosting, Cloud Computing, Cloud Data Services, Network Management, Virtualization, Web Hosting, PaaS, Cloud Infrastructure, Cloud Services, Computing, Cloud Storage, Cloud Security, File Sharing, IT Management |
| 35 | Speech Recognition - Recruitment | 38 | Speech Recognition, Recruitment, Professional Services, Crowdsourcing, Consumer, Knowledge Management, Optimization, Performance, B2B, API, Engine, Process, Offer, Language, Global, Commerce, Point of Sale, Discovery, Document Management, Data Science, Service Provider, Business Development, Planning, SME, Web Application, Machine, Workflow, Web Platform, Helping, Provider, Advisory, Order, Organisation, Employee, Techscale200, Cloud-Based, Future, Customization |

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