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DIGITAL CONVERGENCE: EXAMINING THE DISSOLUTION OF INDUSTRIAL AND TECHNOLOGICAL BOUNDARIES

Research Paper

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Abstract

Digital convergence is frequently discussed in research. The concept of convergence describes how formerly separate areas are increasingly merging. So far, however, we have only a rudimentary understanding of digital convergence for several reasons. First, digital convergence is not clearly conceptualized and used differently across contexts. Second, we have little insight into what is converging and at what pace. We conceptualize digital convergence by arguing that its sociotechnical nature requires jointly considering technical and social aspects. Our analysis of a longitudinal patent data set covering 31 years and 677,045 patents from 124 industries shows that (1) industry boundaries defined by the Standard Industrial Classification (SIC) are dissolving as companies interact with technological knowledge outside their industrial boundaries. (2) Specific technology classes defined in the International Patent Classification (IPC) increasingly cite - and converge with - other technology classes. We close by highlighting promising avenues for future research on digital convergence.

Keywords: Digital convergence, Patent analysis, Digital innovation, Technological distance, Digital transformation

1 Introduction

Digital technology leads to rapid changes in the competitive environment (Karimi and Walter, 2015), requiring organizations to transform established structures and routines (Wessel et al., 2021). In particular, digital technology requires a new perspective on the established modular product architecture towards a layered modular product architecture (Yoo et al., 2010). Whereas the modular logic describes the tight interlocking of different physical components, the layered modular architecture consists of four layers (devices, networks, services, contents), which are only loosely coupled and can be updated and recombined easily (Yoo et al., 2010). The ability to recombine different components flexibly within and across the layers offers nearly endless possibilities for new value creation (Henfridsson et al., 2018). Since the four layers of digital technology do not require product-specific knowledge, existing technological, organizational and even industrial boundaries are increasingly blurring (Lusch and Nambisan, 2015; Nambisan et al., 2017).

These blurring boundaries lead to different forms of *convergence*, which in the most general sense is the "[m]erger and blending of previously separate entities or fields into one" (Hund et al., 2021b, p. 9). When formerly disparate technologies and use contexts are converging to create innovative products (for example, internet-, communication-, and payment-capabilities in smartphones) (Yoo et al., 2012), these technical changes also have far-reaching social implications, for example, at the industrial level,

where companies have to engage with knowledge from different industries and even find themselves competing in new markets. Traditional business expansion describes how companies enter a new industry by competing with incumbents under the same industry regulations, whereas convergence describes how organizations compete while drawing on different resources and acting according to different industry regulations (Seo, 2017). For example, the acquisition of Skype has put Microsoft in direct competition with incumbent companies in the telecommunication sector (Yoo et al., 2010). Thus, extant literature argues that digital technology generally drives convergence across various levels and domains, not only in highly digitalized domains (cf. Yoo et al., 2012; Tilson et al., 2010; Seo, 2017).

However, in light of the "general dearth of empirical and theoretical analyses of digital convergence" (Tilson et al., 2010, p. 751), some even conclude that: "[c]onvergence, as a phenomenon, has been an overused and over-hyped term" (Bonnet and Yip, 2009, p. 53). While previous research has discussed various forms of convergence due to digital technology (e.g., Yoo et al., 2012; Seo, 2017; Lyytinen et al., 2016), we have only a rudimentary understanding of the concept for two reasons. First, while convergence is currently applied across various contexts such as products (e.g., Yoo et al., 2012), devices and networks (e.g., Tilson et al., 2010), as well as entire industries (e.g., Seo, 2017), *digital* convergence is often referenced but not clearly conceptualized. For example, a recent review on convergence highlights the "the advent of the so-called digital convergence" (Sick and Bröring, 2022, p. 4) but does not define how the concept differs from other types of convergence in the context of technology. Therefore, in a first step towards the creation of 'next-generation' IS theory (Burton-Jones et al., 2021), we develop a conceptualization of digital convergence by highlighting its sociotechnical nature, which requires considering "technical artifacts as well as the individuals/collectives that develop and use the artifacts in social […] contexts" (Sarker et al., 2019, p. 696). Accordingly, digital convergence comprises the dissolution of technological boundaries (i.e., the technical side) *and* the dissolution of market or industrial boundaries (i.e., the social side). Second, due to a lack of empirical validation, we have little insight into what is converging and at what pace. Hence, while it is possible that technological or industrial domains are converging on a larger scale, it is also possible that convergence is limited to only a few high-profile examples. Moreover, to date, we do not know whether convergence is occurring at the same pace and scale in every industry or whether industries embrace or resist convergence relative to other industries.

Using a longitudinal analysis of patent data spanning 31 years, 677,045 patents, and 12,956,753 patent comparisons from 124 industries, we can show that (1) industry boundaries as defined by the Standard Industrial Classification (SIC) are increasingly but differentially dissolving as companies interact with technological knowledge from outside their industrial boundaries. (2) There are specific technology classes, defined in the International Patent Classification (IPC), that increasingly cite – and thus converge with - other technology classes.

The next section provides an overview of existing literature on convergence before outlining our method. We then present our results and discuss their theoretical implications. Finally, we discuss our findings and highlight the sociotechnical nature of digital convergence. We conclude by developing promising avenues for future research.

2 Theoretical Background

IS research frequently highlights that digital technology drives convergence on various levels, such as the product and industrial level (e.g., Yoo et al., 2012; Nambisan et al., 2017; Seo, 2017) but in general, convergence "can be driven by market pull, technology push or regulatory push/pull or a combination" (see Sick and Bröring, 2022, p. 5). The concept of convergence is frequently used (Bonnet and Yip, 2009), especially since "[t]echnological progress, particularly in the realm of ICT, is often mentioned as one of the main sources to start and feed convergence processes" (Sick and Bröring, 2022, p. 5).

For example, since the seminal article of Kodama (1992), the concept of technology convergence has received considerable attention across various disciplines. Technology convergence is "defined as the spillover and blending of technological knowledge across previously distinct disciplines" (Jeong et al.,

2015, p. 842). While IS research does not refer to technology convergence, most types of convergence addressed in IS research are closely related to or direct consequences of technology convergence. At the product level, digital technology facilitates technology convergence since it exhibits a layered modular architecture, which "[…] extends the modular architecture of physical products by incorporating four loosely coupled layers of devices, networks, services, and contents" (Yoo et al., 2010, p. 724). Since each layer's specific physical and digital components are only loosely coupled, they can be combined and recombined at ease. For example, on the device layer, there is the hardware (physical component) but also the software (digital component) necessary to control and use the hardware (Henfridsson et al., 2018).

Traditionally, specific devices were tightly coupled with specific networks and services (Seo and Sherif, 2009). However, in the case of digital technology, the components across the four layers are only loosely coupled and can be flexibly combined and recombined (Yoo et al., 2010). This flexibility is characteristic for digital innovation and shakes up established assumptions about innovation since product boundaries cannot be defined upfront (Henfridsson et al., 2018; Kallinikos et al., 2013). Recombining digital and physical components results in the creation of smart products, which drive two types of convergence on the product level. First, *device convergence* occurs since smart products bring together various functions related to information processing, previously held by multiple devices (Tilson et al., 2010). For example, "a smartphone can afford voice call, photo taking, games, and many other capabilities that a user could possibly need (e.g., emulating beer drinking, serving as a flashlight)—all on a single device" (Yoo et al., 2012, p. 1399). Second, there is *network convergence* since a single network can transmit and support basically any type of information by an almost unlimited amount of smart products (Tilson et al., 2010).

Furthermore, convergence decreases the "distance between applied science and technology development" (Curran et al., 2010, p. 387) by bringing together knowledge from various disciplines, which, on the industrial level, drives *digital business convergence* (Seo, 2017). Here, digital technology enables organizations to experiment with new product features (Austin et al., 2012) to identify new product-market combinations (Curran et al., 2010). By bringing together technologies from various backgrounds, organizations encounter a distribution of control over and knowledge about a digital innovation across multiple actors – a phenomenon Yoo et al. (2010) termed *doubly distributed*. Doubly distributed means that (1) control over digital innovation does typically not reside within one company but is distributed across various actors, and (2) knowledge about the digital innovation is distributed across various disciplines (Yoo et al., 2010). Since control over and knowledge about a digital innovation is not held by a single company, close collaboration with external actors and engagement with increasingly distant areas of knowledge is no longer optional (Lyytinen et al., 2016; Boland et al., 2007). The pressure to engage with increasingly distant areas of knowledge fosters new approaches to access and combine different types of knowledge (Hund et al., 2021a), which is leading to blurring organizational boundaries (Nambisan et al., 2017) and to the convergence of entire industries where firms are competing in the same market but draw from a different set of resources and are regulated by different industrial regulations (Tilson et al., 2010; Seo, 2017).

Thus, digital convergence encompasses technical and social aspects, which must be considered jointly. In the context of this paper, we, therefore, define digital convergence as the merger of technological knowledge across established technical and social boundaries. Technical boundaries are defined by the IPC classification, social boundaries are defined by the SIC classification.

A better understanding of digital convergence would therefore provide important insights when trying to understand novel products that transcend established product and industry boundaries or when defining organizational strategies. The same for new forms of industry regulation, for example, "should Vodafone (a British multinational telecom operator) consider Skype as its rival even though it does not have the same license nor is it affected by the same regulations (e.g., taxation) as Vodafone?" (Seo, 2017, p. 690).

3 Methodology

In the following, we first define patents and address the logic behind patent classification systems before explaining the necessary steps in data collection, cleaning, and analysis.

3.1 Patent data

Patents have long been established as an objective, non-financial indicator to measure the value of innovation and relevant factors influencing innovation. Among others, patents have been used to analyze the role of software patents on firm value (Chung et al., 2019; Chung et al., 2015), how organizational networks affect innovation outcomes (Ahuja, 2000; Ahuja and Katila, 2004), and how lone inventors perform in comparison to collaborative efforts (Ahuja and Katila, 2004). Recently, patents have also been used to uncover the positive impact of digital mergers and acquisitions on firm performance (Hanelt et al., 2021). A patent can be understood as a "temporary monopoly awarded to inventors for the commercial use of an invention" (Jaffe et al., 1998, p. 185). To organize different types of patent domains, the International Patent Classification (IPC) system provides a structure of four different levels (Section, Class, Subclass, Group), as depicted in Figure 1 below. These patent categories can be used to measure whether a patent is cited from a similar technological field or whether the patented technologies are from completely different fields. Patents in a particular patent category may be considered more similar than those in other patent categories (Jaffe, 1986; Kay et al., 2014).

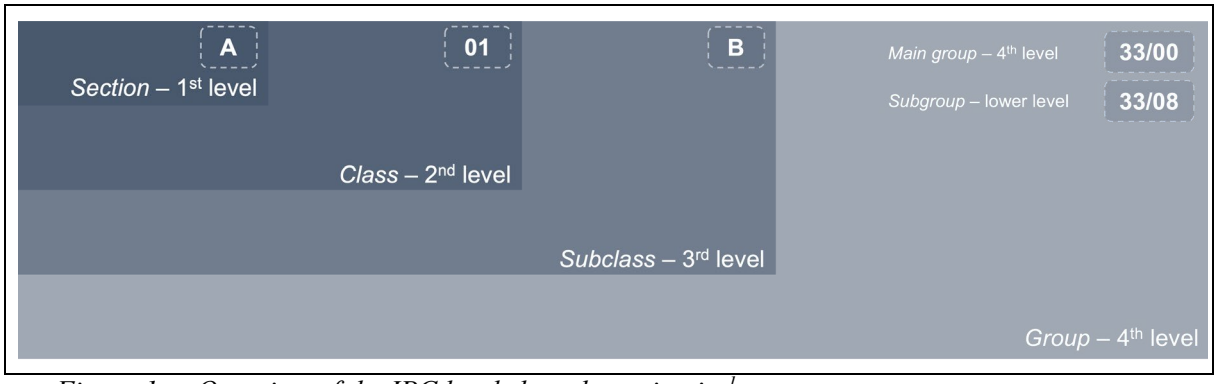

Figure 1. Overview of the IPC levels based on wipo.int[1]

To collect the required data, two main data sources are accessed: Patent data from the USPTO (United States Patent and Trademark Office) and Standard Industrial Classification (SIC) from "Electronic Data Gathering, Analysis, and Retrieval system" (EDGAR) of the Security and Exchange Commission (SEC).

The publicly available patent data of the USPTO is accessed via its archive BDSS (Bulk Data Storage System) [2]. Available patent data was downloaded in XML format and imported, processed, and loaded into a MySQL database. We focus on the 500 most capital-intensive companies in the U.S. as represented in the Standard & Poor's 500 Index (S&P500), a capitalization-weighted market index measuring the stock performance of the 500 strongest companies listed on the U.S. stock exchanges. The index changes whenever the underlying stock price (and thus, the cumulative market value) changes (Kawaller et al., 1987). The index data used for this work was taken from the website markets.businessinsider.com[3], which provides real-time stock market data. Furthermore, the associated SIC codes of each company filing patents are obtained through a web crawler that searches the EDGAR[4]

[1] https://www.wipo.int/classifications/ipc/en/ [last accessed: 06.07.2020]
[2] https://bulkdata.uspto.gov/ [last accessed: 12.11.2021]
[3] https://markets.businessinsider.com/index/s&p_500 [last accessed: 02.01.2020]
[4] https://www.sec.gov/edgar/searchedgar/companysearch.html [last accessed: 12.11.2021]

system. SIC codes are four-digit numeric codes issued by the U.S. government to corporate entities to identify the company's primary business. The classification was developed to facilitate data collection, presentation, and analysis and promote consistency and reproducibility in the display of statistical data gathered by a variety of private organizations and state agencies. The SIC system covers all branches of the economy (Haas, 1977) and divides the economy into 11 divisions, divided into 83 two-digit main groups, which are further divided into 416 three-digit industry groups and finally into 1005 four-digit industries[5]. For our purposes, the primary US-SIC code of each company is used since it indicates the primary line of business of a company. According to the SEC, the code definition that generates the company's highest revenue at a given location in the past year determines the primary SIC code of a company. After collecting all the necessary S&P500 data via a crawler, we merged it with the patent data to construct our final data set.

3.2 Data Cleaning

Five data cleaning procedures have to be performed after collecting and merging the patent and company data to obtain a workable data set, as described in Figure 2.

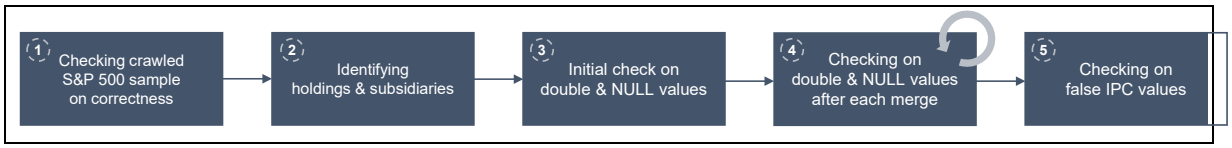

Figure 2. Data Cleaning Process

(1) In a string check, the entries of the searched companies are checked for a match with the respective entry of the recognized company. Since the crawler saves the data in a CSV format, the check was performed in Microsoft (MS) Excel. However, the program itself can only detect unique matches. There are marginal differences in the available data, e.g., between the search term "Facebook" and the found company "Facebook Inc.". In particular, the legal additions to company names lead to errors during verification. Therefore, an additional add-in called "Fuzzy Lookup" for MS Excel is loaded, which can calculate the match in percent. In total, 29 incorrect entries of the 504 companies are identified. These companies marked as incorrect are manually searched again in the EDGAR database to correct the errors. In most cases, the error is that the searched company is not prioritized first by the website but since the crawler selects the first search entry, such errors can occur and must be corrected manually. In addition, the S&P500 index occasionally lists several shares of the same company, as companies may bring different shares to market that differ in price, number and voting rights per share. Class A shares are more expensive and have more voting rights per share than Class B and C shares[6]. Since the shares belong to the same company despite their different classifications, they are combined into one company for later analysis. This concerns the companies Alphabet Inc (Class A/C), Discovery Inc (Class A/C) and Under Armour Inc (Class A/C).

(2) So-called M&As (Merger and Acquisitions), Holdings, and simple name changes were manually coded and streamlined. For example, the holding “Alphabet Inc” was assigned the alias “Google” since it represents the wholly-owned subsidiary Google LLC, formerly known as Google Inc. (3) The different datasets are merged and checked for double and NULL values across all relevant variables. (4) Subsequently, the individual datasets are checked for duplicates and NULL values after each merge. Empty cells, incl. cells containing an empty “ “ string, are flagged with NULL and excluded from further processing. (5) Finally, the data set is checked again for correctness, and individual patents are excluded if, for example, there are faulty IPC classes. This concerns especially older patents. The final dataset

[5] https://www.sec.gov/info/edgar/siccodes.htm [last accessed: 12.11.2021]

[6] https://www.investopedia.com/terms/c/classashares.asp [last accessed: 12.11.2021]

contains 13,095,311 patent comparisons, which can be evaluated over the years from 1989 to 2019 by inspecting their IPC classes.

3.3 Data Analysis

Technology convergence is measured by using the so-called technological distance between patents. Patents are filed for various technologies, which are categorized within different IPC classes. Technological distance describes how far different technology fields are apart from each other based on differences in the IPC classes, which is a key indicator of understanding innovation (Breschi et al., 2003). For example, if the cited patents originate from the same technological environment (e.g., within the same subgroup on the 4th level as depicted in Figure 1), the technological distance is small and indicates incremental innovation. This small distance implies that existing technology is enhanced or improved within the same technological environment (Kay et al., 2014). If the cited patents originate from rather different technological environments (e.g., from different 1st level sections), they differ more clearly i.e., show a higher technological distance, which indicates a rather radical innovation (Olsson, 2005). To frame it in our words, it indicates technology convergence which refers to the combination of technological knowledge across previously distinct disciplines (Jeong et al., 2015).

Data analysis aims to calculate the technological distance between a patent and the patents it cites. The mathematical basis for calculating this technological distance is explained. Then the technical implementation of the data evaluation is discussed. The technological distance between a patent and its cited patents is calculated by comparing the respective IPC classes. To do so, and since patents may have multiple IPC classes assigned, we focus on the primary IPC class to avoid overweighting individual patents. The IPC classes of the existing patents are divided into these four levels (IPC^n), according to Figure 1, and their respective levels are compared to calculate the distance (IPC^n_{DIST}). For example, the first level of the original patent is compared with the first level of the cited patents. The same is repeated for the 2nd, 3rd, and 4th level. The distance value ($TECH_{DIST}$) is based on the formula of (Caviggioli, 2016; Trajtenberg et al., 1997):

$$TECH_{DIST} = IPC1_{DIST} * w1 + IPC3_{DIST} * w2 + WIPO5_{DIST} * w3 + WIPO35_{DIST} * w4$$

$$with\colon w1 = w3 > w2 = w4$$

Compared to the WIPO (World Intellectual Property Organization) classification, which groups all 4-digit IPC codes into 35 fields with activities belonging to 5 macro areas (Electrical Engineering, Instruments, Chemistry, Mechanical Engineering, and Other Fields), the IPC classification allows a significantly more granular analysis. Therefore, instead of the combination of IPC and WIPO, only the IPC classes are used for analysis.

The weights wn are ordered hierarchically, which means that the weighting for the 1st level of the IPC hierarchy is weighted stronger than the weighting for the 2nd level, et cetera. Since the respective four hierarchy levels of the IPC class are equidistant, the concluded weights w in the technological distance formula are set to 0.4, 0.3, 0.2, and 0.1 for $w1$, $w2$, $w3$, and $w4$, respectively. After these adjustments, the following formula and conditions for calculating the technological distance result:

$$TECH_{DIST} = IPC1_{DIST} * w1 + IPC2_{DIST} * w2 + IPC3_{DIST} * w3 + IPC4_{DIST} * w4$$

$$with\colon IPC^n_{DIST} \in \{0,1\}$$

$$with\colon IPC^{n+1}_{DIST} \neq 0 \; for \; IPC^n_{DIST} = 1$$

$$with\colon w1 > w2 > w3 > w4$$

$IPC1_{DIST}$, $IPC2_{DIST}$, $IPC3_{DIST}$ and $IPC4_{DIST}$ are dummy values equal to 1 if the compared patents have different IPC sections (first level), IPC classes (second level), IPC subclasses (third level), or IPC groups (fourth level).

Furthermore, the distance between two sub-levels, i.e., levels 2, 3, and 4, can only be the same (value = 0) if the parent level does not differ, i.e., also has the value 0. The following example illustrates this condition: The two IPC classes, A01B33 and A02B33, are given. This results in the value 0 on level 1 ($IPC1_{DIST}$), since both levels are identical (A). Level 2 ($IPC2_{DIST}$) has the value 1 because the levels are different (01, 02). Level 3 ($IPC3_{DIST}$) (B) and Level 4 ($IPC4_{DIST}$) (33) are identical, but only if they are not considered in the context of the entire IPC class. Since both classes already differ at level 2, they cannot have the same value in the hierarchically subordinate levels. Thus, the value 1 is obtained for level 3 and level 4. The technological distance for the filtered patents is calculated, based on the formula defined above. The distance value is stored and is thus always associated with the respective patent number. After calculation, all distance values are added up. The sum of all distance values is then divided by the number of analyzed patents. The resulting quotient reflects the technological distance of the filtered patent scope:

$$\frac{\sum_{i=1}^{n} TECH_{DIST_i}}{\sum n}$$

After the program code is executed, the result of the quotient, the comparisons between primary and cited patents, and the number of analyzed patents is obtained. The latter serves to get a better understanding of the analyzed data.

4 Results

The analysis yields two key findings: First, most industries as defined by the SIC classification, increasingly transcend industrial boundaries by engaging with increasingly distant technological knowledge. Second, specific technology classes defined by the IPC classification are converging by increasingly citing patents from other IPC classes.

4.1 Transcending Industrial Boundaries By Engaging With Increasingly Distant Areas of Expertise

Our first key result shows that most industries increasingly transcend their established boundaries (as defined by the SIC classification) to engage with more distant areas of expertise (as defined by the IPC classification). Specific industries are typically characterized by their respective customers and products, with products being based on dominant technologies typically used in that industry. Thus, when technological distance increases within an industry, the dominant technology is increasingly complemented or extended by technologies typically prevalent in other industries. By calculating the number of primary patents, the number of total patent comparisons (the comparison of each primary patent with all its cited patents), the ratio of cited patents (how many patents a primary patent cites on average for this year), and the technological distance for every single year within the period of 1989-2019, we can depict the general increase in technological distance. Table 1 provides an exemplary overview of the analyzed period in five-year increments.

Year	No. Primary Patents	No. Comparisons	Ratio of Cited Patents	Technology Distance
2019	51,382	1,075,741	20.936	0.456
2014	42,385	1,055,255	24.897	0.440
2009	22,436	466,145	20.777	0.410
2004	18,750	275,379	14.687	0.420
1999	11,649	125,373	10.763	0.387
1994	8,006	61,900	7.732	0.390
1989	5,288	29,400	5.560	0.391

Table 1: Overview of the analyzed periods in five-year increments

Figure 3 below illustrates the increased technological distance per year when not differentiating between different SIC codes from 1989 to 2019. In addition, the calculated linear model is shown with the darker dashed line. As indicated by the increasing numbers depicted in column five of Table 1, the overall technological distance within the sample across all industries is increasing.

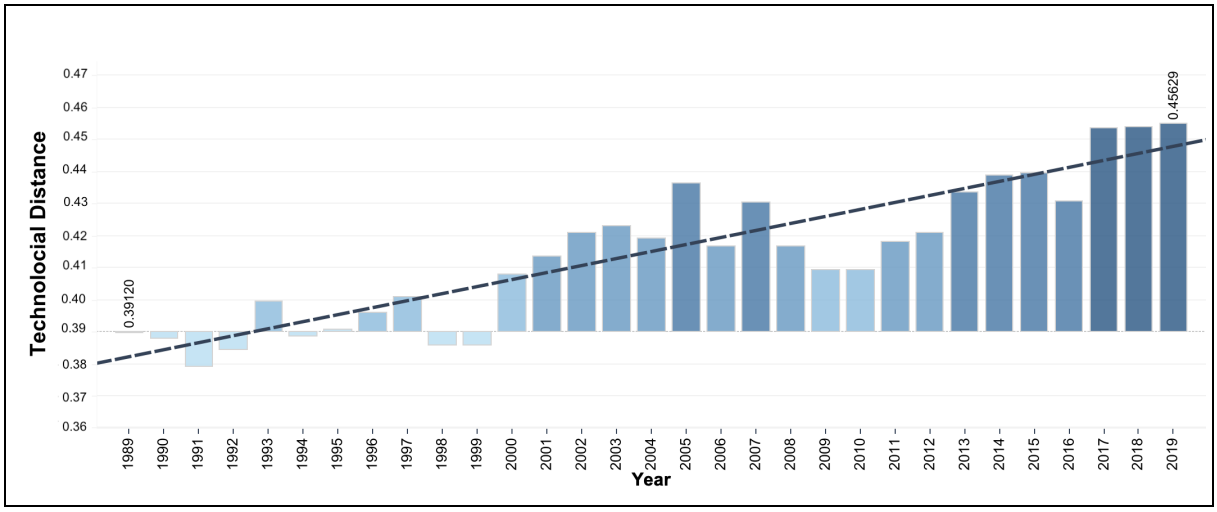

Figure 3. Increasing technological distance per year across all SICs

By considering the three-digit SIC codes, we also gain a more detailed insight into the changes in the individual industries. Figure 7 below shows the changes in technological distance parallel to the number of published patents over 31 years analyzed for all SIC codes with at least 20 values per year for technological distance. The top two quadrants show industries with an increasing technological distance between 1989 and 2019 in their patents, combined with a decreasing number of published patents (top left) or an increasing number (top right). The bottom two quadrants show industries with decreasing technological distance, on the one hand with a decreasing number of new patents per year (bottom left), on the other hand with an increasing number (bottom right).

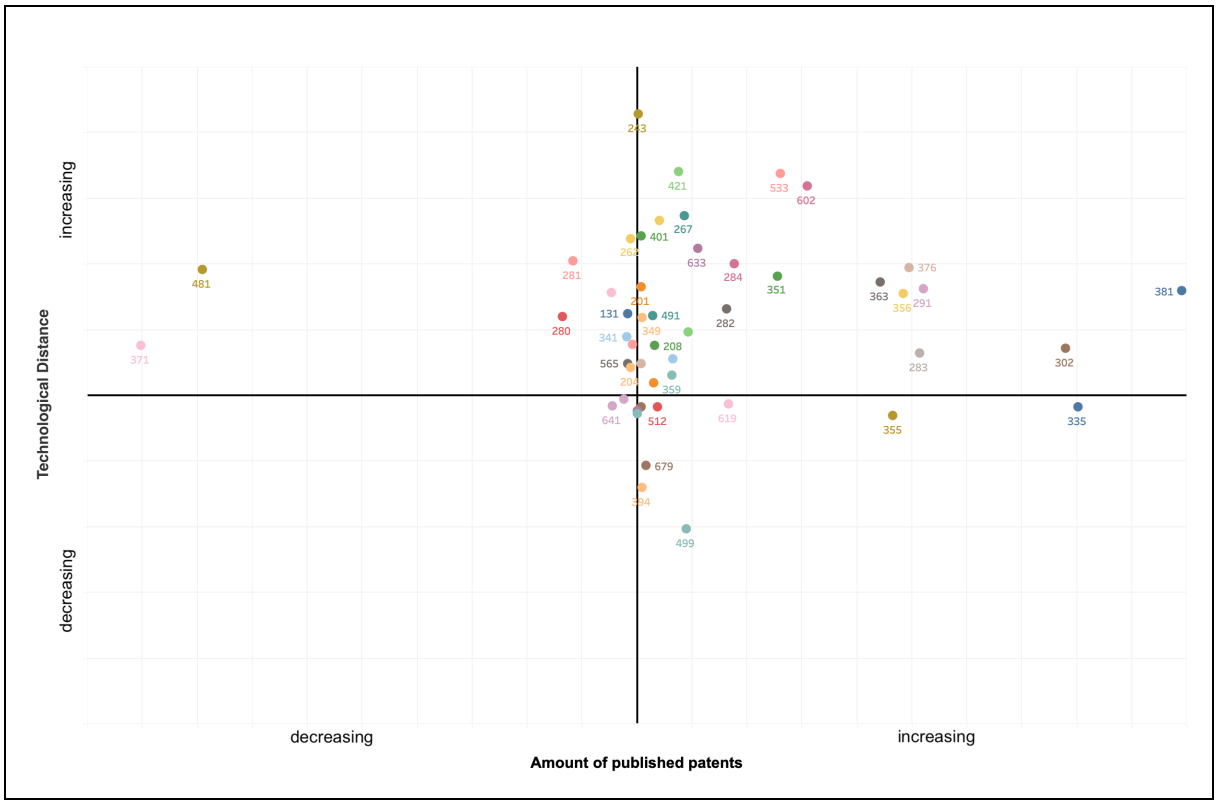

Figure 4. Technological distance and number of published patents per SIC

The results show the varying extent of the technological distance between different industry groups. Overall, 46 out of 62 industries have seen an increase in technological distance in their patents from 1989 to 2019. The more vertically centered the industries, the smaller the increase/decrease in published patents over this period. In many cases, the increase in technological distance is accompanied by an increase in published patents (upper right quadrant). Industries 384, 366, 367, 737, and 357 are not shown in Figure 4 because they are much further to the right in the upper right quadrant and show an increase in technological distance and a very large increase in published patents. However, this is not always the case. 371 (motor vehicles and motor vehicle equipment) and 481 (telephone communications) stand out in particular as they show both an increase in technological distance in combination with a sharp decrease in published patents.

4.2 Technology Convergence: Citation Patterns Between Different IPCs

We now turn to the convergence of specific technologies defined by the IPC. As displayed in Figure 1, the IPC is "a hierarchical system in which all technical knowledge for the field of inventions is divided into sections, classes, subclasses, main groups, and subgroups, in descending order of hierarchy" (DPMA 2020).

Looking only at the highest level of the hierarchy[7] (i.e., the *section* level, ranging from A-H), each IPC section most frequently cites patents from its own first-level IPC section. For example, patents classified in IPC section H (Electricity) most often cite other patents classified in section H. However, looking more closely at the second level of the hierarchy (i.e., the *class* level), we can see that some sections also frequently cite technology classes from other sections. For example, section H also cites 422,042

[7] For a full overview of all IPC sections and classes: https://www.wipo.int/classifications/ipc/ipcpub/?notion=scheme&version=20210101&symbol=none&menulang=en&lang=en&viewmode=f&fipcpc=no&showdeleted=yes&indexes=no&headings=yes&notes=yes&direction=o2n&initial=A&cwid=none&tree=no&searchmode=smart [last accessed: 12.11.2021]

patents from G6 (Computing; Calculating or Counting). Figure 5 below shows the three most frequently cited technology classes at the second level for each section. Each bar is labelled with the total number of patents cited.

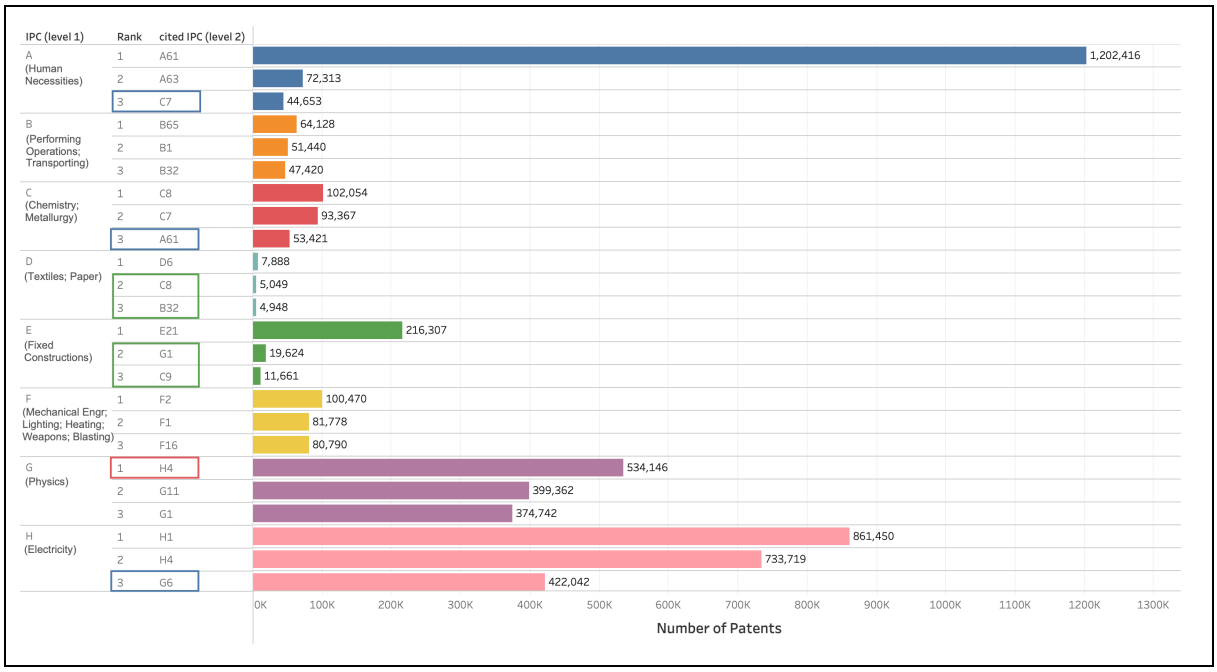

Figure 5. Most frequently cited second level class per first-level section

While the three most frequently cited IPC classes (2nd level) in sections B (Performing operations, Transporting) and F (Mechanical Engineering, Lighting, Heating, Weapons, Blasting) are from the same main section, other sections frequently cite classes from other sections. For example, the third most frequently cited classes in Sections A (Human necessities), C (Chemistry, Metallurgy), and H (Electricity) each come from a different section (marked in blue). In Sections D (Textiles, Paper) and E (Fixed constructions), only the most frequently cited class stems from the same section, whereas the second and third most frequently cited classes are from other sections (marked in green). The most cited technology class in section G (Physics) is from another section (marked in red). These results already indicate increasing convergence between different technology sections, even at the first hierarchical level. For example, within section G (Physics), there is a strong trend towards implementing knowledge from section H (Electricity) or, more specifically, from class H4 (Electric communication technique).

Furthermore, when moving the analysis to the second level of the IPC hierarchy, we can see which specific technology classes cite other technology classes. Figure 6 below depicts the three most commonly cited technology classes, excluding self-citations for all eight sections. For example, we can now see that within section H (Electricity), particularly the class H4 (Electric communication technique) heavily cites patents from G6 (Computing; Calculating or Counting), which explicitly includes various digital technologies. At the same time, patents within G6 also cite patents from H4 to a high degree, indicating a strong trend toward (digital) convergence between these two technology classes.

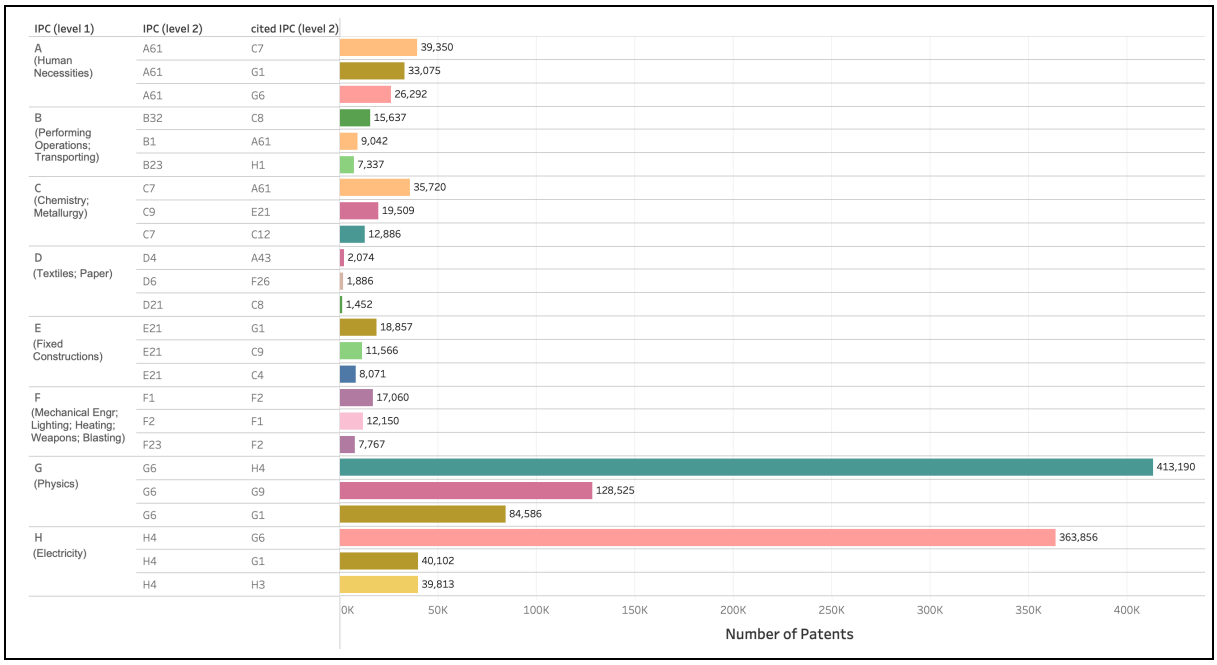

Figure 6: Most frequently cited IPC class per second-level IPC class

5 Discussion

In the following, we first discuss the implications of our findings and potential limitations before presenting some avenues for future research.

5.1 Implications

Our investigation began by arguing that digital convergence is a sociotechnical phenomenon that encompasses the technical dimension as indicated by the increasing convergence of different IPC classes, as well as the social dimension as indicated by organizations located in different markets (defined by the SIC), who are increasingly transcending their established industrial boundaries to access more distant technological knowledge. Therefore, our conceptualization of digital convergence highlights the need to jointly consider technical *and* social aspects, which has been recommended to examine sociotechnical phenomena (Sarker et al., 2019). To address both aspects, we build upon the general concept of technology convergence, which is about transferring technological knowledge to formerly disparate contexts (Jeong et al., 2015). The IPC classification is used to identify knowledge transfer between different technology classes to examine the technical side. The SIC classification is used to identify knowledge transfer between different industrial fields to examine the social side. Digital convergence as a concept is therefore closely related to the concept of technology convergence but enables a conceptual differentiation between technical and social aspects. Therefore, we are in line with Tilson et al. (2010, p. 749), who argue that "we need to distinguish carefully *digitizing* - a technical process - from *digitalization* - a sociotechnical process of applying digitizing techniques to broader social and institutional contexts".

Based on our empirical findings, we make two key contributions: First, our findings corroborate the theoretical discussions from extant research regarding the dissolution of industrial boundaries (i.e., the social side) (cf. Seo, 2017; Nambisan et al., 2017; Tilson et al., 2010). We show that organizations within specific industries, defined in the SIC, access, on average, more distant knowledge domains (see Figure 3). Since industries are usually defined in terms of their specific markets and products, with the products being based on the dominant technologies used in that industry, an increasing technological distance indicates that technologies from other areas of expertise increasingly complement the dominant

technology. Furthermore, while we show that the average technological distance is increasing over the years, this is not the case in every industry. In fact, there exists a remarkable spread among different industries, as depicted in Figure 4. Our results show that convergence occurs across various industries at a different pace and scope. Individual industries (e.g., 371 & 481) even engage with technological knowledge from increasingly distant areas of expertise despite a sharp decrease in published patents. This could indicate that the published patents within these industries are the basis for increasingly radical innovation rather than incremental innovation.

Second, our findings also support the argument that digital phenomena such as digital innovation "regularly exhibit *convergence* […], requiring the combination of heterogeneous knowledge" (Hanelt et al., 2021, p. 8). Thus the phenomenon of convergence, which has been theoretically investigated numerous times (e.g., Yoo et al., 2012; Lyytinen et al., 2016; Fichman et al., 2014), is, in fact, empirically observable. Our analysis reveals that some technology sections heavily draw on other sections' insights even on the highest level of the IPC hierarchy. For example, the most frequently cited technology class in the technology section G (Physics) stems from section H (Electricity), as depicted in Figure 5. When considering the second level of the IPC hierarchy, we can see that specific technology classes located in different technology sections such as G6 (Computing; Calculating or Counting) and H4 (Electric communication technique) frequently cite each other. This supports the increasing convergence of technology classes across technological boundaries in general and digital convergence since G6 explicitly encompasses digital technologies.Furthermore, the increasing "spillover and blending of technological knowledge across previously distinct disciplines" as illustrated by the increasing technological distance (Jeong et al., 2015, p. 842), addresses an interesting tension in IS literature. On the one hand, knowledge is increasingly distributed across specific actors from different domains (Yoo et al., 2012) but, on the other hand, knowledge is "interwoven, increasingly inseparable […], questioning the fault lines between established knowledge domains" (Hanelt et al., 2021, p. 6). According to our results, the general trend supports the latter argument that a clear distinction between different knowledge domains is increasingly difficult.

As with any research, this study has limitations that provide opportunities for future research. Our initial sample consists of almost 13 million patent comparisons, however, this only represents a fraction of the globally accessible patent data. The limitation to the S&P500 was chosen to demonstrate the methodology on a prominent sample and hopefully encourage future, more encompassing research. Moreover, the analyzed sample may still contain residual noise in the data set despite a thorough cleaning phase. Furthermore, the current dataset represents a snapshot. The companies included in this study are from the S&P500 as of January 2020. The S&P500, as a moving index, may add or remove companies on an ongoing basis. In addition, new patents are filed every year and must be included in future analyses. Besides, we focused on the primary IPC class of each patent, which can also be addressed in future analyses. Finally, while we show how industries transcend their established boundaries, an in-depth analysis of the convergence of specific industries is beyond the scope of this study. Apart from these limitations, our results allow us to make suggestions for future research by providing guidance on where and how relevant data can be collected and analyzed. This allows future studies to differentiate between companies and obtain an even more granular picture of digital phenomena.

5.2 Avenues for future research

Considering the sociotechnical nature of digital convergence enables future research to emphasize "the technical or the social side […] without losing sight of the other" (Hund et al., 2021b, p. 13). In the following, we develop some avenues for future research.

As discussed above, we measured technology convergence using the classic patent measurement "technological distance". Technological distance describes how far different technology fields are apart based on differences in the IPC classes, which is a key indicator of understanding innovation (Breschi et al., 2003). A small technological distance implies that a certain patent only cites other patents from

the same technological domain (Kay et al., 2014). In that case, the technological knowledge domain boundaries reflected by the IPC categorization are kept and reinforced. If a patent cites other patents from different domains, such as a patent of "Electricity" citing another patent from "Physics", the technological distance is larger, and different technological domains are combined to form a new patent. In this example, the new patent is an "Electricity" patent but informed by "Physics" sections. In these cases, technological boundaries are crossed, and knowledge from different domains converges. Apart from using patent data to measure technology convergence, we came across further opportunities that provide promising avenues for future research. While technological distance reflects technology convergence, it might also be used as a starting point to measure the heterogeneity of knowledge which extant research puts forth as the main characteristic of digital innovation. Heterogeneity, similar to technological distance, could be measured based on patent citations. An adapted measure for technological diversity (Vasudeva and Anand, 2011) seems appropriate. Technological diversity can be measured at different levels of analysis: patent class, company, industry. For patent class, all citations of all patents of a certain patent class are pooled and compared to the number of citations referring to patents within the respective patent class. The higher the number, the more citations come from outside the respective patent class. In addition, the number of citations could be differentiated by cited patent classes. This measure would account for heterogeneity in how many other patent classes and how many patents from outside a respective patent class are cited across all patents of a respective patent class. It would measure how heterogeneous the knowledge basis of certain patent classes is. In a similar vein, heterogeneity of the knowledge base of a certain company or industry could be measured.

To measure industry convergence (Yoo et al., 2012), two data sources are needed: One for industry classifications and another one for patents to pool all patents of a certain industry, e.g., based on 2-digit or 3-digit SIC codes, and identification of all patent citations within the respective industry. Within the cited patents, the filing company is identified, and in another step, the corresponding primary SIC code of the filing company. Finally, the analysis regarding the industry under investigation shows how many of its patent citations relate to patents filed by companies of other SICs and to which SICs these companies belong. Eventually, it can be demonstrated how strongly industry A relies on patents filed by companies of industry B, and so on. If the cross-citation between certain industries is quite strong, the technological basis across these industries seems similar. This, in turn, drives the convergence of products based on these technologies and may result in the convergence of industries exhibiting overlapping product-market combinations. Accordingly, such measures could reflect industry convergence in line with recent studies in IS, indicating that the increasing digitalization blurs industrial boundaries and challenges the separation of firms and industrial categories.

In a similar vein, it would be possible to identify groups of companies that are part of different industries but exhibit a technological basis that is more similar to one another than the technological basis of companies outside of these groups. However, they may belong to the same industry as specific companies of the group. Thus, firms sharing similar characteristics across industries form a new set of competitors that may also explain differences in measures such as sales growth across classic industries (Seo, 2017).

6 Conclusion

In this paper, we take a closer look into the phenomenon of digital convergence. Our analysis of a longitudinal patent data set covering 31 years and 677,045 patents from 124 industries allows us to make two key contributions: First, industry boundaries as defined by the Standard Industrial Classification (SIC) are increasingly dissolving as companies increasingly interact with technological knowledge from outside their industrial boundaries (Figure 3 and 4). Second, as defined in the International Patent Classification (IPC), specific technology classes increasingly cite - and thereby converge with - other technology classes (Figure 5 and 6). Thereby, we highlight that digital convergence is a sociotechnical phenomenon encompassing both technical and social change and conclude by outlining particularly promising avenues for future research.

7 References

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