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The Influence of Digitization on Technological Convergence

Completed Research Full Paper

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Abstract

Convergence is a frequently discussed phenomenon of digital innovation and is reflected in the merging of previously separate areas. Convergence takes place on various levels, one of them being technological convergence which serves as a main factor for the other levels of convergence, e.g. product or industry convergence. The phenomenon of technological convergence has already been theoretically studied. However, in an increasingly digitized world, we do not understand how and to what extent technological convergence is driven by digitization and how this effect becomes empirically manifest. In our analysis of a longitudinal patent data set consisting of over four million patents, we compare digital vs. non-digital patents and thus are able to show and quantify the impact of digitization on technological convergence. We show that (1) technological convergence is not solely a fundamentally digital phenomenon and (2) boundaries between digital and non-digital patents become blurrier over time. We conclude by indicating future avenues for research on the impact of digitization.

Keywords

Digitization, Technological Convergence, Patent Analysis, Digital Innovation.

Introduction

Digital innovation has significantly altered the way new products and services are designed and developed (Nambisan et al. 2017). It refers to creating or adopting and exploiting a valuable new idea (e.g., product, service, process, or business model) by incorporating digital technology (Hund et al. 2021). Video meetings for global collaboration and 3D printers for quick prototype validation are just some examples. According to Yoo et al. (2010), relying on digitization, or the encoding of analog information into digital format, is a necessary yet not sufficient condition for digital innovation. Digitizing is a technical process making it distinct "from digitalization – a sociotechnical process of applying digitizing techniques to broader social and institutional contexts" (Tilson et al. 2010, p. 749). Digitalization requires and builds on digitization, nonetheless, to a certain extent, both contribute individually to digital innovation (Hund et al. 2021).

Digital innovation results in two phenomena: (1) generativity, referring to the use of an invention for a previously unforeseen application or the recombination of individual components, which in turn leads to the creation of novel products and services, and (2) convergence, referring to the merging of previously separate areas, whether being markets and industries (Seo 2017), products and services, or technologies (Tilson et al. 2010; Yoo et al. 2012), while the convergence of industries and products are also based upon the latter, technological convergence (Hacklin et al. 2009).

Technological convergence is defined "as an autonomous, serendipitous underlying phenomenon, where previously distinct technologies increasingly start to share common technological properties" (Hacklin et al. 2009, p. 726) resulting in these formerly distinct technologies now being recognized as a common set (Hacklin et al. 2009; Rosenberg 1963). Nowadays, this is reflected in the convergence of physical and digital artifacts (Yoo et al. 2012), caused by integrating digital components in tangible products (Hund et al. 2021), for instance, a smartphone's capability of communicating using several antennas, taking pictures by integrating a camera, or paying wirelessly in supermarkets by integrating near field communication (NFC) sensors (Yoo et al. 2012).

Thus, the convergence of physical and digital technology has led to changes in product architecture, resulting in a multi-layered modular architecture comprising "four loosely coupled layers of devices, networks, services, and contents created by digital technology" (Yoo et al. 2010, p. 724) successively facilitating different technologies to converge across and within those layers with one another. The flexible recombination of components allows for almost infinite possibilities for creating new value (Henfridsson et al. 2018).

The phenomenon of convergence has been theoretically studied several times (Lyytinen et al. 2016; Tilson et al. 2010; Yoo et al. 2012) and the convergence of technologies is seen as "a key driver of market/ industry convergence" (Jeong and Lee 2015, p. 79; based on Hacklin 2008). Based on this, empirical studies have been carried out which show that technological convergence is indeed taking place. Not only are industries increasingly citing knowledge from more distant areas, but new technologies are also increasingly building on more distant technologies (Caviggioli 2016; Müller et al. 2022). However, despite these first descriptive empirical insights, we still do not have a deeper understanding about how and to what extent technological convergence is driven by digitization. This results in our research question:

RQ1: To what extent does digitization drive technological convergence?

We aim to answer this question by conducting a longitudinal study of patent data. Technological convergence is measured by calculating the technological distance within its assigned technological classification using the International Patent Classification (IPC) (Caviggioli 2016; Müller et al. 2022). The sample is split into two groups of digital vs. non-digital patents to show the impact of the technical facet, i.e., digitization, on technological convergence.

Theoretical Background

Technological Convergence

Convergence, reflected in the merging of previously separate areas, constitutes itself on various levels (Hund et al. 2021). One of them, technological convergence, delineates the blend of formerly disparate technological domains into a novel unified paradigm. It transcends mere technological fusion, wherein two distinct technologies coalesce into either one of both (Jeong and Lee 2015). Instead, "convergence describes a process, where objects move or stretch farther from their prior and discrete spots, to a new and common place" (Curran and Leker 2011, p. 258). This integrative process is propelled by the convergence of disparate elements towards uniformity, resulting in the synthesis of innovative functionalities through the amalgamation of diverse technological components.

Technological convergence manifests as an independent and fortuitous event, characterized by the gradual emergence of common technological features among formerly disparate technologies (Hacklin et al. 2009; Rosenberg 1963). This encompasses both previously addressed technical functionalities and novel applications, necessitating the development of innovative products forged through the convergence of multiple technological components (Rosenberg 1963). Notably, technological convergence encompasses technologies from diverse application domains. For instance, the confluence of technological components originating from sewing machine manufacturing and weapons production culminated in the creation of a universal milling machine in the 19th century industrialization in the United States, thereby laying the groundwork for subsequent industry-specific advancements, such as those in the automotive sector (Rosenberg 1963).

In an increasingly digitized world, technological convergence is catalyzed by digitization, the process of encoding analog information into digital format. Digitization enables physical products to be programmed and to communicate, lowering barriers for separate technologies to converge (Yoo et al. 2012). This means that distinct technologies share more and more technological properties (Hacklin et al. 2009), such as re-

programmability, data homogenization, and self-referentiality, which are properties of digital technologies (Yoo et al. 2010). Consequently, digitization can be construed as an integral driver of technological convergence, facilitating convergence at the product level (Tilson et al. 2010). Digital technologies are integrated in a vast variety of products, each characterized by diverse use cases, e.g. image capturing in industry cameras and smartphones. This further leads to convergence on the device level, such as the integration of a camera in the smartphone (device convergence) which in turn engenders versatility, enabling the application of such products across disparate markets and industries (industry or market convergence), united by a shared technological subset (Seo 2017; Tilson et al. 2010; Yoo et al. 2012). An example of industrial convergence is Microsoft's acquisition of Skype, allowing the company to compete with telecommunication companies such as Vodafone (Yoo et al. 2012). Throughout each level of convergence, antecedent convergence levels serve as catalysts (Jeong and Lee 2015), thereby engendering a causal relationship stemming from technological convergence. Ultimately, it can be posited that technological advancement and innovation serve as enablers, while technological convergence emerges as a pivotal driver for industry and market convergence (Hacklin 2008; Jeong and Lee 2015). Not only does it signify a departure in terms of the type of convergence invoked, but it also underpins the foundation for industry and market convergence.

Related Patent Literature

"[…] (A) granted patent protects the inventor, at least for a period of time, from imitation" (Ernst 2003, p. 233). Patents are filed in one or multiple jurisdictions, e.g. in the United States (US) at the United States Patent and Trademark Office (USPTO) or in Europe at the European Patent Office (EPO). Patents filed in multiple jurisdictions will be aggregated into a so-called patent family, defined as "[…] a collection of patent documents that are considered to cover a single invention. The technical content covered by the applications is considered to be identical" (European Patent Office 2017, p. 4).

A patent application is a meticulous process that requires more than just a comprehensive explanation of the invention. It also necessitates the provision of standardized patent metadata that aids in its classification. It is vital to ensure that all the required data are included accurately as they facilitate efficient patent search and analysis. This metadata structure remains standardized for every patent, regardless of the type of innovation, and encompasses details such as the applicant, inventor, owner, year of application, backward citations (i.e., patents cited within the invention disclosure), and technology classification, among others. The latter is classified using the International Patent Classification (IPC) system which provides a four-level structure (Section, Class, Subclass, Group) to organize various patent domains. These categories can be employed to assess whether a patent results from a similar set of technological knowledge or entirely different technology fields. Patents within a particular category may be considered more similar than those in other categories (Jaffe 1986; Kay et al. 2014).

Patent metrics have been considered a reliable and objective non-financial measure to evaluate the degree and value of innovation and its associated factors for decades (Schmookler 1966; Trajtenberg 1990). Researchers have utilized patents to investigate the innovativeness of startups (Kim and Kogut 1996), the impact of software patents on firm value (Chung et al. 2015, 2019), the effect of organizational networks on innovation outcomes (Ahuja 2000; Ahuja and Katila 2004), and the comparative performance of lone companies or inventors versus collaborative efforts (Ahuja and Katila 2004; Almeida et al. 2002). Further, patent analysis revealed the positive impact of digital mergers and acquisitions on firm performance (Hanelt et al. 2021).

Concerning digital innovation, information systems (IS) scholars use various patent metrics to explore the impact of information technology (IT) on innovation performance (e.g., Joshi et al. (2010)). Kim et al. (2016) use patent count data to capture a firm's technological capability, proving a significantly stronger shift from internal investments in research and development (R&D) to corporate venture capital investments, for technology leaders in the IT industry. Gomez et al. (2017) ascertain that IT investments strengthen the relationship between open-innovation strategies and product invention. Inmyung Choi et al. (2021) show that a higher dependency of a chief executive officer's wealth on their company's stock return volatility encourages the CEO to support more IT innovation and is reinforced by their higher levels of IT education and expertise. By measuring patent count and stock market performance, Guo et al. (2023) find firms with solid investments in IT generate more patents with greater value.

At least since Lerner's (1994) measure of patent scope, IPC codes are commonly used for empirical analysis (Dechenaux et al. 2008; Fischer and Ringler 2014; Laursen et al. 2017), proofing the valuable use of the

four-digit IPC classes to measure technological breadth and diversification. Further, IPC codes can be used to calculate the technological relatedness of collaborating firms (Schildt et al. 2005) as well as technological novelty (Verhoeven et al. 2016; Wirsich et al. 2016). Combined with patent citation data, citation pattern differences between technology fields (Ernst and Omland 2011) and the radicalness of novel technologies are captured (Laursen et al. 2017). Lately, Caviggioli (2016) and Müller et al. (2022) have explored convergence based on the empirical analysis of IPC codes, serving as the foundation for our methodology.

Methodology

Utilizing patent metadata, our longitudinal study delves into the realm of technological convergence. This section on methodology includes detailing the sample and data collection process, as well as explaining how the level of technological convergence is measured.

Sample and Data Collection

The calculations of technological convergence are based on two samples: (1) digital patents and (2) non-digital patents. In our previous section on Technological Convergence, we discussed that digitization plays a pivotal role in driving technological convergence and are thus distinguishing between digital and non-digital patents based on that concept. We expect that patents classified as digital will exhibit greater levels of technological convergence compared to non-digital patents. Digital patents are identified using the 23 keywords from Hanelt et al. (2015, 2021) (such as "digital", "digital technolog*", or "connectivity"). All keywords are applied to the patent's title, abstract, and claims. For non-digital patents, the complementary set of keywords is used accordingly. We focus on patent families in the US with the status 'granted'. This ensures that only patents are analyzed that have come into force and have not been rejected by the USPTO. In addition, all patents must have been filed between 2000 and 2019. The latter restriction ensures that sufficient granted patent data is available each year, as the grant process takes at least 18 months.

Patent data is accessed using PatentSight, a database of LexisNexis Intellectual Property Solutions, retrieving patent families granted in the US. As explained before, a patent family is the aggregation of patent documents covering an identical invention. Patent family data contains metadata of all related patent documents, ensuring a comprehensive dataset. By analyzing at the family level, rather than at the level of individual patent documents, the occurrence of duplicate documents covering the identical invention is avoided. Further, patent families incorporate patent metadata for all jurisdictions a patent is filed in, therefore avoiding the risk of neglecting global patent portfolios (Ernst and Omland 2011).

For each patent family, the following data is retrieved: (1) the patent family number to uniquely identify the patent family and to avoid duplicates, (2) the owner, and (3) the owner ID, i.e. the company owning the patent, (4) filing date and (5) grant date of the patent family, (6) prior art, i.e. the patent documents the respective patent family cites, (7) IPCs and (8) number of IPCs per IPC level to subsequently calculate the (9) technological diversity of each patent family. Subsequently, data is cleaned by excluding null values in the IPC field and checking for duplicates.

The final sample contains 430,889 digital patent families and 3,786,648 non-digital patent families. The sample of patents cited by all digital patent families consists of 3,376,714 patent families. These digital backward citations are included to gain insights about the extent to which the patent families build upon digital technologies. Here, the temporal limitation was lifted as, e.g., digital patents filed in 2000 cite patent families published earlier.

Measuring Technological Convergence

Technological convergence is measured by calculating the technological distance within assigned IPCs of a patent family. The more heterogeneous the assigned IPC codes are, the higher the technological distance is. Accordingly, a higher technological distance indicates that disparate technologies are converged in the respective patent family. As various technologies are patented and classified within different IPC classes, the disparity between different technology fields is established by the discrepancies in their IPC classes. This plays a vital role in determining innovation comprehension (Breschi et al. 2003).

As an illustration, if all assigned IPC codes of a patent family stem from the same technological domain (for instance, within the same group at the fourth level), the technological distance is minimal, indicating a

homogenous set of technologies. Conversely, suppose the assigned IPC codes originate from diverse technological domains (implied by multiple assigned IPC sections on the first level). This case is shown in the upper part of Figure 1. In that case, the technological distance among the three IPCs assigned to the shown patent family US2009194104.A1 is greater, indicating a higher level of heterogeneity of technologies (Olsson 2005). This suggests technological convergence, the amalgamation of technological expertise across previously distinct disciplines (Jeong and Lee 2015).

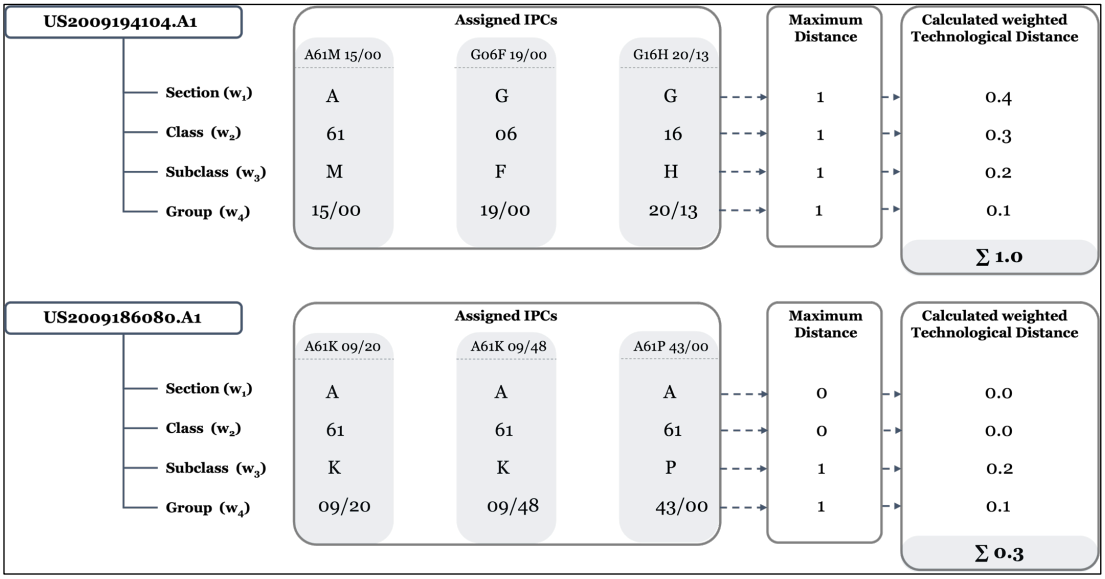


Figure 1. Calculation of Technological Distance per IPC Level for Two Exemplary Patent Families

This study builds upon previous calculations of technological distance (Caviggioli 2016; Müller et al. 2022) by determining the maximum distance of IPCs assigned to a particular patent family through a comparison of its assigned IPC levels. The variable 'number of IPCs per IPC level' represents unique IPCs and a technological heterogeneous patent family is identified if this variable exceeds 1, indicating that multiple IPCs have been assigned to it. By comparing this variable across all levels of the IPC, we can determine at which level the technological distance is evident. The IPC hierarchy employs a hierarchical weighting system, which prioritizes the weighting (w) for the 1st level over the 2nd level, and so on. As all four hierarchy levels of the IPC class are equally distant, the weights in the technological distance formula are determined to be 0.4, 0.3, 0.2, and 0.1 for w_1, w_2, w_3, and w_4, respectively.

The distance between two sub-levels, specifically levels 2, 3, and 4, can only be equivalent (value = 0) under the condition that the parent level is also uniform and has a value of 0. In other words, if the parent level possesses a distinct value, then the distance between the aforementioned sub-levels cannot be 0.

Results

To gain insights from the derived data set, we performed Welch's two sample t-tests, comparing the mean technological distance of digital vs. non-digital patent families. To aim for higher robustness, we checked for other variables explaining our results, such as the number of patents per year and the number of forward citations per patent family. Subsequently, we describe our key findings.

Significant Difference between Digital and Non-Digital Patent Families

We compared the samples both in total and for each year stratum. The results from the t-test based group comparisons are presented in Table 1 (exemplarily for selected years only). The average technological distance compared between both samples, digital and non-digital, significantly differs from one another. Digital patents have a significantly higher technological distance than non-digital patents. This is confirmed by t-tests for every single year and across all years of the longitudinal study. The latter results in an average

mean of technological distance of 0.612 (digital) vs. 0.572 (non-digital), with the difference being highly significant (p = 0.000). Further, within the digital sample, the mean technological distance is at least 1.71% higher (year 2010) compared to non-digital patents. In all remaining years, this value was exceeded, topping at a 17.34 % higher technological distance (year 2000) within the digital sample compared to non-digital.

Year	# of Non-Digital Patents	# of Digital Patents	Avg. Technological Distance *(Non-Digital)*	Avg. Technological Distance *(Digital)*	Ratio of Technological Distance *(Digital / Non-Digital)*	t-value	p-value
2000	177,810	17,967	0.454	0.532	+17.34%	23.538	0.000
2005	176,648	23,216	0.554	0.605	+9.14%	17.737	0.000
2010	189,980	22,078	0.597	0.607	+1.71%	3.503	0.000
2015	242,981	25,568	0.602	0.639	+6.27%	14.239	0.000
2019	207,912	20,913	0.586	0.636	+8.47%	17.158	0.000

Table 1. Overview of Analyzed Non-Digital and Digital Patent Families in Five-Year Periods

Increasing Technological Distance over Time

The mean technological distance per year is growing for both digital as well as non-digital patent families (see Figure 2), showing that technological distance has increased over the past years, however not only for digital patents.

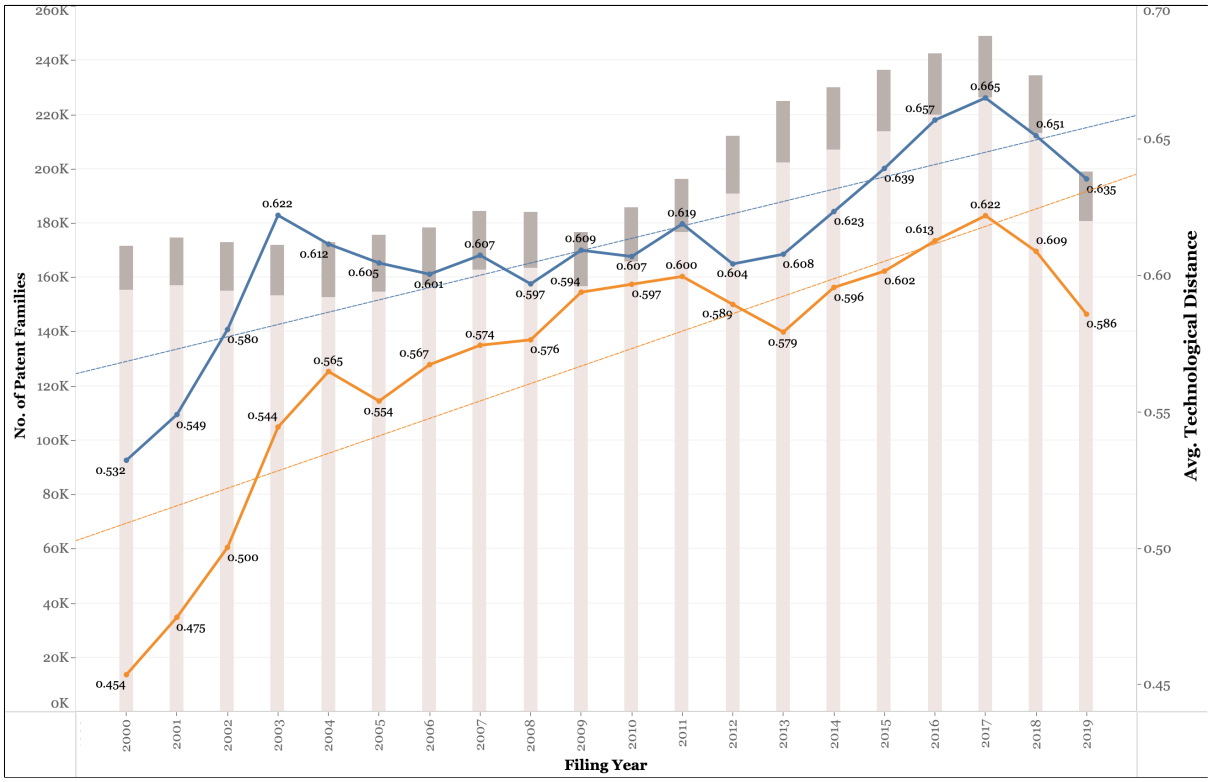


Figure 2. Mean Technological Distance and Number of Patents per Filing Year for Both Digital (blue, dark grey) and Non-Digital (orange, light grey) Patent Families

For both samples, the technological distance is not growing year after year. However, using a linear regression model (dashed line, $p = 0.000$, $R^2 = 0.762$), we find a significant increase in technological distance for both samples across the analyzed filing years. Zooming into single IPC sections, analysis shows that there is a significant increase over the years for every single technology class, except for digital patents with IPC codes of section C (Chemistry, Metallurgy; n = 20,803, p-value = 0.635) which occupies the highest mean technological distance for both digital (0.943) and non-digital (0.885) patents across all IPC sections.

Growing Digital Citation Share in Non-Digital Patents

Delving into data from the non-digital patent sample, the analysis reveals that, from 2000 to 2019, patents defined as 'non-digital' do increasingly cite patents from the digital sample. The digital citation share was 4.24% in 2000 rising to 5.83% in 2019. To confirm this trend, we performed another patent search by applying the keywords from (Hanelt et al. 2015, 2021) to all patents cited by this study's non-digital patent sample. By doing so, digital patent data from before the year 2000 is captured, as this study's digital patent sample is capped to that time. Results show that the share of digital patents cited by patents in the non-digital sample steadily grew significantly ($p = 0.000$) from 3.71% in 1980 to 8.98% in 2019.

In sum, the patent analysis reveals several key findings. One of the most noteworthy findings is that digital patents are more diverse in terms of their IPC codes, resulting in a significantly higher mean technological distance per year when compared to non-digital patents. Additionally, both digital and non-digital patents have seen a significant increase in technological distance over time. Furthermore, the technological distance in digital patent families consistently surpasses that of their cited patents, confirming a rise in technological heterogeneity as measured by IPC codes. Finally, non-digital patents are increasingly citing digital patents.

Discussion

This study aims to empirically answer the research question to what extent digitization drives technological convergence by measuring the technological distance of a patent's assigned IPC codes. Next, we first discuss the implications of our findings and potential limitations followed by avenues for future research.

Our study holds several theoretical implications. First, looking at the digital patent families, our results are in line with existing theory as we find an increase in technological distance, pointing to a growing technological convergence over time (Jeong and Lee 2015; Tilson et al. 2010; Yoo et al. 2010). In addition, we find that technological convergence is not a homogenous process but is different depending on the technology class (IPC). That is, IPC classes show different growth in technological distance. We speculate that the difference is due to characteristics of the specific technology domain, represented by IPCs, where it is difficult or impossible to replace analog components with digital ones. An illustrative example is the fundamental difference between a patented image-capturing software technology and exposure control. While the first patented technology might fully incorporate digitization, the latter might not, as exposure control can involve analog components that are not digitized.

Secondly, we found that technological distance is growing in non-digital patents as well which shows that technological convergence is not solely a fundamentally digital phenomenon. Figure 2 illustrates that technological distance also increases over the years in the non-digital sample. Likewise, although to a lesser extent, increasingly distinct technologies converge with each other. An examination of individual IPCs elucidates this phenomenon. For instance, the technological distance for patent families categorized as technologies from the field of Chemistry and Metallurgy (IPC C) stands at 0.884 (non-digital) and 0.943 (digital), significantly exceeding the overall average. Combined with the observation that technological distance does, in this particular IPC section, not significantly increase due to digitization, we can only speculate that this IPC code pertains to an applied technology. For example, take the patent family US2013123300.A1, "Urea Compounds And Use Thereof For Inhibiting Apoptosis" from our non-digital sample. This invention is about a chemical compound designed for pharmaceutical use and is therefore classified with IPC sections A (Human Necessities) and C. Consequently, the practical protective rights frequently unite distant technologies even without the influence of digitization. This is in line with examples noted in literature such as Rosenberg (1963) but extends the scope of technological convergence stated in IS literature beyond purely digital technologies. The necessity of investigating the phenomenon of technological convergence at the IPC level vividly demonstrates that technological convergence is not a homogeneous phenomenon extending

uniformly across all technology fields. Rather, it underscores the varying degrees of technological convergence across different technology domains.

The third theoretical implication of this study highlights the frequently described phenomenon of "blurring boundaries"(Curran and Leker 2011; Hund et al. 2021; Müller et al. 2022), in our case between digital and non-digital technologies. By analyzing the intersections between the backward citations (prior art) of non-digital patent families and digitally categorized patent families, it becomes apparent that non-digital patent families in more recent years increasingly cite digital patents, i.e. digitized technologies. This indicates that digitization, the technical process of converting analog information into digital format, is proliferating. Since these digital patent families possess different IPC codes than non-digital ones, this diffusion effect is reflected in the technological distance of non-digital patent families. Therefore, digitization itself contributes to technological convergence in non-digital inventions, demonstrating the ubiquity of digital technologies nowadays. The characteristics of digital technologies enable the reuse and recombination of already developed technologies and lower the barrier for digitizing non-digital technologies.

Finally, this paper makes an empirical contribution. Our study demonstrates that and to which extent digitization influences technological convergence. As depicted in Table 1, the technological distance is calculated for digital and non-digital patent families for each year. A higher value of this distance indicates that a patent family encompasses more distant technologies, meaning that separate technologies converge within them. The magnitude of digitization's influence is evidenced by the percentage expansion of technological distance in the digital sample compared to the non-digital sample (Table 1, Column 6). The study reveals that digitization has an impact on technological convergence from the outset of our longitudinal study. It exceeds the distance value of the comparison group, the non-digital sample, for every year since 2000. By enabling the measurement of this influence of digitization on technological convergence, we empirically confirm existing theoretical arguments and thus make a significant contribution to research.

Limitations and Avenues for Future Research

Certainly, this study has potential limitations which are often accompanied by longitudinal patent data studies. First, the sample definition relies on splitting available patent data into digital and non-digital patents. Therefore, we used the keywords defined by Hanelt et al. (2015, 2021) who applied those keywords to the automotive industry. As our study does not have that industry focus, further keywords might have been applicable, providing a broader scope on digitization and eventually leading to a more thorough digital sample. Yet, the sample definition by using keywords within the patent full texts provides a better boundary definition than relying on IPC codes which might have blurred boundaries. Second, analyzing patent data has some limitations: This study only focuses on patent families granted in the US. This may result in a data set neglecting regional inventions in other parts of the world, e.g. patents only filed in Europe or China. However, by analyzing on patent family level we tried to reduce this US-centric approach and include metadata from other jurisdictions as well (Ernst and Omland 2011). If an invention is protected in other jurisdictions, additionally to the US, the assigned metadata is included in our sample. Third, we used the formula of Caviggioli (2016) and Müller et al. (2022) to calculate the technological distance between assigned IPC codes. In contrast to both research articles, we applied this formula within a patent family and did not incorporate direct citation data. Last, while we can show the impact of digitization on technological convergence, we are not differentiating between different industries and results are not generalizable for every single industry.

Hence, this study provides several avenues for future research. First, as the trend of digitization continues, search filter keywords may include the latest technological trends to identify digital patents and lift the restriction on USPTO grants. Second, the analysis may not only incorporate patent metadata but also consider the patents' content, i.e. the full-text. Third, technological convergence may be measured using other existing formulas on technological heterogeneity like Lerner's patent scope (Dechenaux et al. 2008; Fischer and Ringler 2014; Lerner 1994) or technological diversity of patents using the Herfindahl index (Conti et al. 2014; Gambardella and Torrisi 1998). Lastly, future research might complement this study's findings by incorporating industry-specific data, like Standard Industrial Classification (SIC) codes, to examine the effect of digitization on certain industries.

Overall, we believe that this study and future research building on our results will contribute to a deeper and better understanding of how digitization propels innovation through its specific potentials of generativity and convergence.

References

Ahuja, G. 2000. "Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study," *Administrative Science Quarterly* (45:3), pp. 425–455.

Ahuja, G., and Katila, R. 2004. "Where Do Resources Come from? The Role of Idiosyncratic Situations," *Strategic Management Journal* (25:8/9), pp. 887–907.

Almeida, P., Song, J., and Grant, R. M. 2002. "Are Firms Superior to Alliances and Markets? An Empirical Test of Cross-Border Knowledge Building," *Organization Science* (13:2), pp. 147–161.

Breschi, S., Lissoni, F., and Malerba, F. 2003. "Knowledge-Relatedness in Firm Technological Diversification," *Research Policy* (32:1), pp. 69–87.

Caviggioli, F. 2016. "Technology Fusion: Identification and Analysis of the Drivers of Technology Convergence Using Patent Data," *Technovation* (55–56), pp. 22–32.

Chung, S., Animesh, A., Han, K., and Pinsonneault, A. 2019. "Software Patents and Firm Value: A Real Options Perspective on the Role of Innovation Orientation and Environmental Uncertainty," *Information Systems Research* (30:3), pp. 1073–1097.

Chung, S., Han, K., Animesh, A., and Pinsonneault, A. 2015. "Competitive Impacts of IT Innovation: An Empirical Analysis of Software Patents in the IT Industry", *in Proceedings of the 36th International Conference on Information Systems*, Fort Worth, USA, pp. 1–18.

Conti, R., Gambardella, A., and Mariani, M. 2014. "Learning to Be Edison: Inventors, Organizations, and Breakthrough Inventions," *Organization Science* (25:3), pp. 833–849.

Curran, C.-S., and Leker, J. 2011. "Patent Indicators for Monitoring Convergence – Examples from NFF and ICT," *Technological Forecasting and Social Change* (78:2), pp. 256–273.

Dechenaux, E., Goldfarb, B., Shane, S., and Thursby, M. 2008. "Appropriability and Commercialization: Evidence from MIT Inventions," *Management Science* (54:5), pp. 893–906.

Ernst, H. 2003. " Patent Information for Strategic Technology Management," *World Patent Information* (25:3), pp. 233–242.

Ernst, H., and Omland, N. 2011. "The Patent Asset Index – A New Approach to Benchmark Patent Portfolios," *World Patent Information* (33:1), pp. 34–41.

European Patent Office. 2017. "Patent Families at the EPO," *https://link.epo.org/web/Patent_Families_at_the_EPO_en.pdf* (last accessed on 29.02.2024).

Fischer, T., and Ringler, P. 2014. "What Patents Are Used as Collateral? - An Empirical Analysis of Patent Reassignment Data," *Journal of Business Venturing* (29:5), pp. 633–650.

Gambardella, A., and Torrisi, S. 1998. "Does Technological Convergence Imply Convergence in Markets? Evidence from the Electronics Industry," *Research Policy* (27:5), pp. 445–463.

Gomez, J., Salazar, I., and Vargas, P. 2017. "Does Information Technology Improve Open Innovation Performance? An Examination of Manufacturers in Spain," *Information Systems Research* (28:3), pp. 661–675.

Guo, F., Li, Y., Maruping, L. M., and Masli, A. 2023. "Complementarity Between Investment in Information Technology (IT) and IT Human Resources: Implications for Different Types of Firm Innovation," *Information Systems Research* (34:3), pp. 1259–1275.

Hacklin, F. 2008. "Management of Convergence in Innovation: Strategies and Capabilities for Value Creation Beyond Blurring Industry Boundaries," in Contributions to Management Science, Physica-Verlag, Heidelberg, Germany.

Hacklin, F., Marxt, C., and Fahrni, F. 2009. "Coevolutionary Cycles of Convergence: An Extrapolation from the ICT Industry," *Technological Forecasting and Social Change* (76:6), pp. 723–736.

Hanelt, A., Firk, S., Hildebrandt, B., and Kolbe, L. M. 2021. "Digital M&A, Digital Innovation, and Firm Performance: An Empirical Investigation," *European Journal of Information Systems* (30:1), pp. 3–26.

Hanelt, A., Piccinini, E., and Gregory, R. W. 2015. "Digital Transformation of Primarily Physical Industries - Exploring the Impact of Digital Trends on Business Models of Automobile Manufacturers," in *Proceedings of the 12th International Conference on Wirtschaftsinformatik, Osnabrück, Germany*.

Henfridsson, O., Nandhakumar, J., Scarbrough, H., and Panourgias, N. 2018. "Recombination in the Open-Ended Value Landscape of Digital Innovation," *Information and Organization* (28:2), pp. 89–100.

Hund, A., Wagner, H.-T., Beimborn, D., and Weitzel, T. 2021. "Digital Innovation: Review and Novel Perspective," *The Journal of Strategic Information Systems* (30:4), pp. 1–39.

Inmyung Choi, Sunghun Chung, Kunsoo Han, and Pinsonneault, A. 2021. "Ceo Risk-Taking Incentives and It Innovation: The Moderating Role of a Ceo's It-Related Human Capital," *MIS Quarterly* (45:4), pp. 2175–2192.
Jaffe, A. 1986. "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits and Market Value," No. w1815, pp. 1–33.
Jeong, S., and Lee, S. 2015. "What Drives Technology Convergence? Exploring the Influence of Technological and Resource Allocation Contexts," *Journal of Engineering and Technology Management* (36), pp. 78–96.
Joshi, K. D., Lei Chi, Datta, A., and Shu Han. 2010. "Changing the Competitive Landscape: Continuous Innovation Through IT-Enabled Knowledge Capabilities," *Information Systems Research* (21:3), pp. 472–495.
Kay, L., Newman, N., Youtie, J., Porter, A. L., and Rafols, I. 2014. "Patent Overlay Mapping: Visualizing Technological Distance: Patent Overlay Mapping: Visualizing Technological Distance," *Journal of the Association for Information Science and Technology* (65:12), pp. 2432–2443.
Kim, D. J., and Kogut, B. 1996. "Technological Platforms and Diversification," *Organization Science* (7:3), pp. 283–301.
Kim, K., Gopal, A., and Hoberg, G. 2016. "Does Product Market Competition Drive CVC Investment? Evidence from the US IT Industry," *Information Systems Research* (27:2), pp. 259–281.
Laursen, K., Moreira, S., Reichstein, T., and Leone, M. I. 2017. "Evading the Boomerang Effect: Using the Grant-Back Clause to Further Generative Appropriability from Technology Licensing Deals," *Organization Science* (28:3), pp. 514–530.
Lerner, J. 1994. "The Importance of Patent Scope: An Empirical Analysis," *The RAND Journal of Economics* (25:2), pp. 319–333.
Lyytinen, K., Yoo, Y., and Boland Jr., R. J. 2016. "Digital Product Innovation within Four Classes of Innovation Networks: Digital Product Innovation," *Information Systems Journal* (26:1), pp. 47–75.
Müller, L., Hund, A., and Wagner, H.-T. 2022. "Digital Convergence: Examining the Dissolution of Industrial and Technological Boundaries," in *Proceedings of the 30th European Conference on Information Systems,* Timișoara, Romania, pp. 1-16.
Nambisan, S., Lyytinen, K., Majchrzak, A., and Song, M. 2017. "Digital Innovation Management: Reinventing Innovation Management Research in a Digital World," *MIS Quarterly* (41:1), pp. 223–238.
Olsson, O. 2005. "Technological Opportunity and Growth," Journal of Economic Growth (10:1), pp. 31–53.
Rosenberg, N. 1963. "Technological Change in the Machine Tool Industry, 1840-1910," The Journal of Economic History (23:4), pp. 414–443.
Schildt, H. A., Maula, M. V. J., and Keil, T. 2005. "Explorative and Exploitative Learning from External Corporate Ventures," *Entrepreneurship: Theory & Practice* (29:4), pp. 493–515.
Schmookler, J. 1966. "Invention and Economic Growth," Harvard University Press, Cambridge, MA.
Seo, D. 2017. "Digital Business Convergence and Emerging Contested Fields: A Conceptual Framework," *Journal of the Association for Information Systems* (18:10), pp. 687–702.
Tilson, D., Lyytinen, K., and Sørensen, C. 2010. "Digital Infrastructures: The Missing IS Research Agenda," *Information Systems Research* (21:4), pp. 748–759.
Trajtenberg, M. 1990. "A Penny for Your Quotes: Patent Citations and the Value of Innovations," *The RAND Journal of Economics* (21:1), pp. 172–187.
Verhoeven, D., Bakker, J., and Veugelers, R. 2016. "Measuring Technological Novelty with Patent-Based Indicators," *Research Policy* (45:3), pp. 707–723.
Wirsich, A., Kock, A., Strumann, C., and Schultz, C. 2016. "Effects of University-Industry Collaboration on Technological Newness of Firms," *Journal of Product Innovation Management* (33:6), pp. 708–725.
Yoo, Y., Boland, R. J., Lyytinen, K., and Majchrzak, A. 2012. "Organizing for Innovation in the Digitized World," *Organization Science* (23:5), pp. 1398–1408.
Yoo, Y., Henfridsson, O., and Lyytinen, K. 2010. "Research Commentary —The New Organizing Logic of Digital Innovation: An Agenda for Information Systems Research," *Information Systems Research* (21:4), pp. 724–735.