Müller, Lukas; Drechsler, Katharina; Wagner, Heinz-Theo; Beimborn, Daniel

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The Role of Technological Convergence and Digitalization for Business Value

Lukas Müller
University of Bamberg, Germany
lukas.mueller@uni-bamberg.de

Katharina Drechsler
University of Cologne, Germany
drechsler@wiso.uni-koeln.de

Heinz-Theo Wagner
Neu-Ulm University of Applied Sciences, Germany
heinz-theo.wagner@hnu.de

Daniel Beimborn
University of Bamberg, Germany
daniel.beimborn@uni-bamberg.de

Abstract

Digital technologies enable vast opportunities for innovation. These innovations, driven by the flexible and modular architecture of digital technologies, blur traditional boundaries and foster the convergence of previously separate technologies and industries. Convergence facilitates new business opportunities and value creation. However, despite the potential of these developments, the extant literature has not fully explored their impact on business value. Our study addresses this gap by analyzing over 3.7 million patent families from 2000 to 2018, using natural language processing and regression analysis. We show that (1) technological convergence is positively linked to patent value and (2) this relationship is enhanced by the integration of digital technologies. Our study provides valuable insights into how technological convergence and the integration of digital technologies are associated with business value, offering new avenues for future research.

Keywords: Digital Technologies, Technological Convergence, Business Value, Patent Analysis, Patent Value

1. Introduction

Digital technologies' unique characteristics, such as their binary representation, data homogenization, reprogrammability, and self-referentiality (Yoo et al., 2012) spur almost limitless opportunities afforded by digital innovation. Digital innovation is increasingly prevalent in our economy and is defined as the generation, adoption, and leveraging of an inherently limitless, value-enhancing novelty (such as products, services, processes, or business models) by integrating digital technologies (Hund et al., 2021). Digital technologies follow a layered modular architecture consisting of four layers (devices, networks, services, content) that are only loosely coupled and can be easily altered and recombined (Yoo et al., 2010). The ability to flexibly recombine various components within and between layers offers companies nearly infinite possibilities for new value creation (Henfridsson et al., 2018).

As the four layers of digital technologies do not require product-specific knowledge, existing technological, organizational, and even industrial boundaries are increasingly blurred (Lusch & Nambisan, 2015; Nambisan et al., 2017). These changes are the result of converging previously separate technologies, markets, industries, or products. For example, smartphones unite antennas for telecommunications, sensors for GPS positioning, and NFC chips for supermarket payments. In theoretical terms, this means that various technologies converge in a smartphone. In that regard, technological convergence – referring to merging previously separate technologies – is considered the main cause for subsequent convergences, such as market or industry convergence (Hacklin, 2008; Jeong & Lee, 2015). Furthermore, the literature argues that technological convergence is accelerated by increasingly incorporating digital technologies into products and processes (Yoo et al., 2012).

Convergence may open up business opportunities across various competitive fields and expand companies' options for value creation (Seo, 2017). Empirically, Caviggioli (2016) shows that first-time cross-citations between technology fields are increasingly occurring over time. Müller et al. (2022) apply patent analyses and find that certain technology fields cite more distant technology fields, which points to the growing convergence of those technology domains over time within patents. However, to date, the literature has neglected to explore the business value of technological convergence, in particular, in combi-

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nation with the increasing use of digital technologies. This results in our research question:

RQ: How are technological convergence and digital technologies related to business value over time?

To answer this question, we analyze over 3 million patent families from the years 2000 to 2018. To capture the impact of digital technologies, we analyze patent abstracts using natural language processing. Using regression analysis, we show that technological convergence is positively linked to patent value, which represents business value, i.e. "the social benefits generated by the innovation in the form of the additional consumer surplus and the profits stemming from the innovation" (Trajtenberg, 1990, p. 173). Furthermore, this link is positively moderated by the integration of digital technologies.

Below, we first examine the related literature on technological convergence and patent value, followed by deriving our hypotheses and research model. Subsequently, we outline our methodology. Then, we present the results of our regression analysis and discuss their implications. We conclude by highlighting avenues for future research.

2. Theoretical background

This section elaborates on related literature by discussing the concept of technological convergence and patent value.

2.1. Technological convergence

Convergence, as described in the merging of previously separate areas due to digital technologies' fundamental characteristics, occurs on various levels (Hund et al., 2021). Digital technologies can store and process any type of information (device convergence) and allow one network to facilitate a wide range of information services (network convergence) (Tilson et al., 2010). The increasing use of digital technologies across industrial sectors has further resulted in industry or market convergence (Tilson et al., 2010; Yoo et al., 2012). Seo (2017) further theorizes about digital business convergence by describing it as the increasing tendency of companies from different industries to compete against each other, while relying on different resources and operating based on different regulation regimes.

Underlying these developments is technological convergence, which involves joining formerly distinct technological domains into novel conjunctions. Notably, in contrast to technological fusion, where two separate technologies combine into a single entity (Jeong & Lee, 2015), technological convergence can be seen as a process of merging two discrete technologies into a new common one, resulting in innovative functionalities (Curran & Leker, 2011). It is characterized by the gradual development of common features among previously distinct technologies (Hacklin et al., 2009; Rosenberg, 1963). Further, this process is considered a directed form of recombination, distinguishing it from general knowledge recombination. As described by Fleming, (2001), Fleming & Sorenson (2001) or Uzzi et al. (2013), combinatorial innovation does not necessitate its components to converge.

Technological convergence is a phenomenon that already existed long before the introduction of digital technologies and their characteristics. For example, in the 19th century, during industrialization, formerly separate technological components of sewing machine manufacturing and weapons production converged in a universal milling machine (Rosenberg, 1963).

However, in today's digital age, technological convergence is accelerated by digitization which is defined as the process of converting analog information into digital format (Tilson et al., 2010). Digitization allows physical products to be programmed and interconnected, reducing barriers for different technologies to merge (Yoo et al., 2012). As a result, distinct technologies increasingly share common properties such as reprogrammability, data homogenization, and self-referentiality, which are inherent to digital technologies, resulting in a layered modular architecture (Yoo et al., 2010). This architecture successively facilitates different technologies to converge with each other across and within those layers. The flexible recombination of components allows for nearly endless possibilities for value creation (Henfridsson et al., 2018).

2.2. Patent value

Patents are filed and granted to temporarily protect the inventor from imitation (Ernst, 2003). They reflect the technologies of the invention, classified by patent offices in the patenting process. This is done using the International Patent Classification (IPC) system, introduced by the World Intellectual Property Organization (WIPO) (WIPO, 2022). A patent family has prevalently multiple IPC codes assigned. IPC codes are structured hierarchically. The first IPC level (section) indicates a broad set of technology domains. Table 1 lists the different first-level IPC codes.

Table 1. IPC sections (WIPO, 2022).

IPC Code (section level)	Description
A	Human Necessities
B	Performing Operations; Transporting
C	Chemistry; Metallurgy
D	Textiles; Paper
E	Fixed Constructions
F	Mechanical Engineering; Lighting; Heating; Weapons; Blasting
G	Physics
H	Electricity

Patents may be filed in multiple jurisdictions, e.g., in the United States at the United States Patent Office (USPTO). Patents that are filed in multiple jurisdictions, but concerning the same invention, are linked to a common 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).

The protection from imitation secured through patents is valuable for companies in the innovation process, in order to gain and protect a potential competitive advantage. Therefore, patents are often used as a yardstick for evaluating the company (Vasudeva & Anand, 2011), as an indicator of its innovation performance (Geerts et al., 2018), or its overall competitiveness (Ernst & Omland, 2011). As previously stated in our introduction, patent value acts as a representation of business value and encompasses all social benefits derived from the innovation, manifesting as increased consumer surplus and the profits resulting from the innovation (Trajtenberg, 1990).

Several indicators reflect a patent's value. In order to use an invention that is patented, one has to find an agreement with the inventor. Besides, new inventions might build upon previous patents, which they must cite accordingly. Therefore, a common approach to capture a patent's value is to count the number of times the patent gets cited by other patents, i.e. forward citations (Funk & Owen-Smith, 2017; Lahiri, 2010; Laursen et al., 2017; Trajtenberg, 1990; Vasudeva & Anand, 2011). To enhance this approach and to cope with "systematic distortions of existing citation-based patent indicators" (Ernst & Omland, 2011, p. 35), Ernst & Omland (2011) normed the count of forward citations to patent office citation practices, the patent family's age, and the average number of citations within its technology fields.

3. Research model

In this section, we derive our hypotheses and combine them into our research model.

We first turn to the relationship between technological convergence and patent value, which serves as our proxy for business value. 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). Patent value is defined as "the future commercial utility that can be extracted from the use of the patent" (European Patent Office, n.d.). With multiple IPC codes assigned, a patent family can combine several IPC sections at once, i.e. a very heterogeneous set of technologies, thus, indicating the technological convergence within this patent family.

The more technologically diverse a patent is, the wider the range of applications it can be applied to (Atanassov, 2016; Harhoff & Wagner, 2009). This enhanced application spectrum offers the opportunity for a patent to be cited by a wider range of patents, thus increasing its value. This leads to our first hypothesis:

h1: Technological Convergence has a positive association with Patent Value

We now turn to the effect of digital technologies, which we measure by using the concept of digital orientation. We argue that digital orientation moderates the link between technological convergence and patent value. Digital orientation refers to the extent to which a patent incorporates, utilizes, or develops digital technologies or components thereof (Drechsler et al., 2023). Digitization, in particular digital technologies' unique characteristics mentioned in Section 2.1., provides a key to enabling the layered modular architecture. Due to the layered modular architecture that allows for high flexibility and adaptability (Yoo et al., 2010, 2012), similar digital technologies are often used in combination with other technologies. For instance, digital devices process any information, which allows them to be used across industries in technologies (Tilson et al., 2010) or patents. Moreover, digital technologies can allow companies to move into new strategic fields and exploit new business opportunities (Seo, 2017). Accordingly, patents relying on digital technologies, as measured by a higher digital orientation, are better positioned to capitalize on the benefits of technological convergence, since they can more effectively combine and converge different technologies and create novel solutions, thereby increasing their overall value. Accordingly, we hypothesize:

h2: Digital Orientation positively moderates the association between Technological Convergence and Patent Value

Figure 1 summarizes our overall research model.

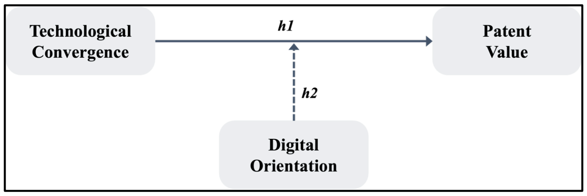

Figure 1. Research model.

4. Methodology

4.1. Sample

Our initial sample consists of 4,256,664 patent families which were filed since 2000 and granted by the USPTO. Patent data was accessed via PatentSight, a database of LexisNexis Intellectual Property Solutions. After initial data screening, we selected the filing years from 2000 to 2018 to ensure an equally distributed number of patents per year. In a separate process, the abstracts of these patents were collected. Using natural language processing and a validated dictionary from Kindermann et al. (2021), we calculated each patent's digital orientation following (Drechsler et al., 2023). Subsequently, all data was merged into one dataset. Finally, the dataset was checked for duplicates and NA values which we excluded. The final data sample consists of 3,782,973 patent families.

4.2. Variables

Table 2 lists all variables utilized in our study, which we delineate below.

Dependent Variable

We measure patent value using the variable technology relevance (Ernst & Omland, 2011). As explained in Section 2.2., this metric enhances the count of forward citations by norming it for patent office citation practices, the patent family's age, and the average number of citations within its technology fields.

Independent Variables

Technological convergence and digital orientation serve as our independent variables.

Technological convergence is measured by calculating the Herfindahl-Hirschman-Index (HHI) for the assigned IPC classes (on subclass-level) of each patent family. HHI is a concentration measure and is inverted with N as the total amount of assigned IPC classes, while n_i represents the unique IPC subclass within N:

$$HHI = 1 - \sum_{i=1}^{N} (\frac{n_i}{N})^2$$

Therefore, 1 indicates full technological heterogeneity while 0 indicates full homogeneity.

The digital orientation of a patent family is defined as the extent to which a patent incorporates, utilizes, or develops digital technologies or components thereof (Drechsler et al., 2023). The measure is computed by following a widely used computer-aided text analysis approach (McKenny et al., 2018). It derives word vectors and word counts using the digital orientation dictionary, which was conceptualized and validated by Kindermann et al. (2021). The dictionary includes around 200 words or terms (e.g., data analytics, internet of things, blockchain). Past studies have demonstrated the robustness of the measure by comparing it to other digitalization measures and word lists (Drechsler et al., 2023; Kindermann et al., 2021). We then aggregated these word counts for each patent family and divided them by the number of words in the abstract to derive a relative measure.

Control Variables

We control for several effects based on existing literature using patent data. First, we take several patent metadata into account, such as the time to grant (Nerkar, 2003), the number of a patent's backward citations (Singh & Fleming, 2010; Vestal & Danneels, 2022), the number of IPC subgroups (Harhoff & Wagner, 2009), and the number of active authorities (Hu et al., 2020). Second, we include dummy variables for each IPC section (IPC level 1) (Hu et al., 2020) and for each filing year to control for effects specific to each IPC section and fixed-year effects.

Table 2. Variable overview.

Theoretical Concept	Variable Name	Description
Dependent Variable		
Patent Value	Technology Relevance	Count of forward citations normed by Patent Office Citation Practices, the patent family's Age, and the average number of citations within its technology fields (Ernst & Omland, 2011).
Independent Variable		
Technological Convergence	HHI	Inverted Herfindahl-Hirschman-Index of a patent family's assigned IPCs (subclass-level) measuring Technological Heterogeneity.
	Digital Orientation	Value between 0 and 1, depending on the occurrences of digital keywords in a patent family's abstract (Drechsler et al., 2023).

Table 2 (continued).

Control Variables		
	Time to Grant	Time, measured in years, between filing date and grant date of a patent family.
	# of Backward Citations	Number of patents cited by the respective patent family.
	# of IPC Subgroups	Number of the patent family's assigned IPCs, on subgroup-level.
	# of Active Authorities	Number of authorities, the patent family is active in.
	IPC Section (dummy, values between A and H)	Dummy which takes value 1 if one of the patent family's assigned IPC classes is in the respective section.
	Filing Year (dummy)	Dummy which takes the value 1 for the patent families filing year.

4.3. Estimation method and robustness checks

Deciding on the correct estimation method is crucial for our analysis and depends on the given data. We noted various effects after an initial check of the previously described variables and their distributions. First, our dependent variable technology relevance, is positive and highly right skewed with a few extreme values. Therefore, we decided to perform winsorization with a threshold of 1%. Further, we choose a Gamma regression model, which can handle the positive skewness and its overdispersion of our dependent variable (McCullagh, 2019).

To enhance the robustness of our model we included dummy variables for each IPC section (A to H) with section G serving as our baseline, due to the highest number of assigned patent families. Additionally, we checked for fixed-year effects, with the year 2000 as the baseline.

In addition, we conducted a thorough analysis to check for correlated values among the independent variables. Table 3 shows a reduced correlation matrix with (1) our dependent variable as well as our independent variables (2) and (3). To ensure the robustness of our findings, we examined potential multicollinearity in our models using variance inflation factors (VIFs). All VIFs are close to 1, showing no sign of multicollinearity.

Table 3. Reduced correlation matrix.

Variable	**Mean**	**SD**	**(1)**	**(2)**	**(3)**
(1) Technology Relevance	0.23	0.32			
(2) HHI	0.30	0.37	-.19 [-.69, .43]		
(3) Digital Orientation	0.10	0.30	-.05 [-.61, .54]	-.15 [-.67, .47]	
Note: M and SD are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates p < .05. ** indicates p < .01.					

5. Results

In the following, we first present descriptive results (5.1. Descriptive analysis) before moving to the model tests (5.2. Regression analysis).

5.1. Descriptive analysis

In the following, we structure the results according to their main insights, starting with descriptive statistics shown in Table 4.

Table 4. Summary statistics.

Variable	**Mean**	**SD**	**Min**	**Median**	**Max**
Technology Relevance	1.515	4.324	0.047	0.950	175.362
Technology Relevance (win)	1.461	2.499	0.115	0.950	8.997
HHI	0.370	0.080	0.000	0.444	1.000
Digital Orientation	0.008	0.000	0.000	0.000	0.500
DO_HHI	0.003	0.000	0.000	0.000	0.222
Time to Grant	3.173	2.424	0.083	2.917	20.667
# Backward Citations	26.630	6,795.575	0.000	15.000	7,033.000
# IPC Subgroups	6.835	34.895	0.000	5.000	247.000
# Active Authorities	2.144	13.549	0.000	1.000	69.000
Note: Technology Relevance represents the values of Technology Relevance before winsorization, while Technology Relevance (win) shows Technology Relevance after winsorization.					

The descriptive statistics for our variables shed light on the data's central tendencies and dispersion. The mean value of technology relevance is 1.515, with a standard deviation of 4.324, indicating significant variability around the mean. The minimum and maximum values of technology relevance are 0.047 and 175.362, respectively, while the median is 0.950, suggesting that the distribution is skewed towards higher values. After winsorization, which reduces the effect of extreme values, technology relevance (win) shows a mean of 1.461 and a standard deviation of 2.499. The minimum value is adjusted to 0.115, the median remains at 0.950, and the maximum value is reduced to 8.997.

The Herfindahl-Hirschman Index (HHI), a measure of concentration, has a mean of 0.370 and a standard deviation of 0.080. The minimum value is 0.000, the median is 0.444, and the maximum value is 1.000, indicating a range from full technological homogeneity to complete heterogeneity. Digital orientation has a mean of 0.008, with low variation as shown by the standard deviation. Its values range from 0.000 to 0.500, with the median at 0.000.

The interaction term of the Herfindahl-Hirschman Index and Digital Orientation (DO_HHI) shows minimal variation, with a mean of 0.003, a standard deviation close to zero, and values ranging from 0.000 to 0.222. The zero value in the number of Active Authorities arises because our sample includes both active and inactive patent families.

Figures 2 and 3 show the distribution of our winsorized dependent variable technology relevance vs. our independent variables HHI and digital orientation. The plots are built upon a randomized subsample of 10,000 data points to increase visibility. Figure 2 contains one plot for each independent variable, including the regression line of our Gamma model.

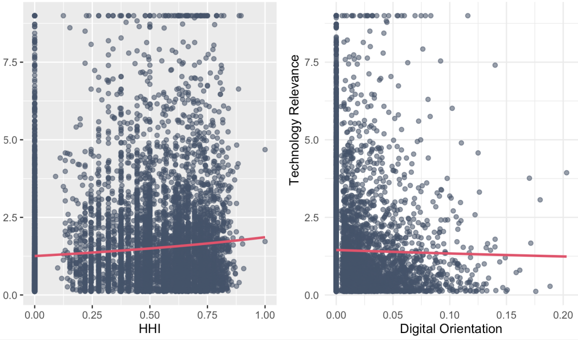

Figure 2. 2D plot for each independent variable.

The scatterplot in Figure 3 is presented from two different angles. Technology relevance is shown on the z-axis, while HHI is displayed on the x-axis, and digital orientation on the y-axis. The coloring refers to the value of technology relevance, reaching from dark (low technology relevance) to light (high technology relevance). The plot reveals that most patents are clustered around the median HHI, indicating different levels of technological convergence and exhibiting a low to medium degree of technology relevance. Additionally, most patents have relatively low digital orientation.

The data also shows a divergence in the degree of technological convergence, with some patent families scoring zero in HHI, indicating complete technological homogenization, nevertheless being able to score high values in technology relevance.

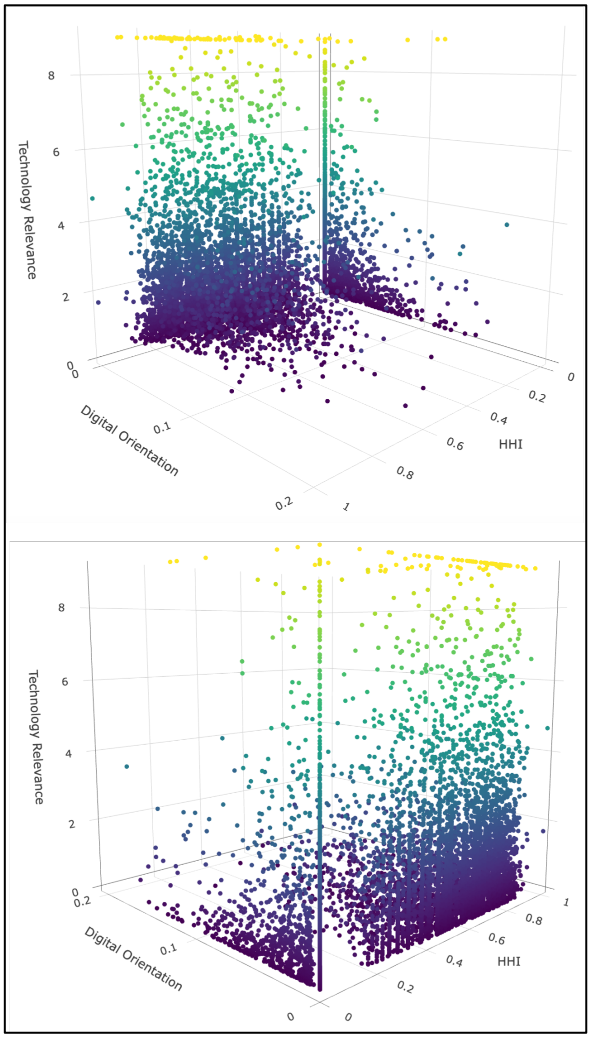

Figure 3. 3D scatterplot of Technology Relevance vs. HHI and Digital Orientation from two different perspectives.

5.2. Regression analysis

Table 5 shows the results for both Model 1 (baseline model) and Model 2. Model 1 is calculated to test hypothesis h1, with HHI as our independent variable. Model 2 is calculated to test h2 and thus includes the interaction term DO_HHI to show the moderating effect of digital orientation.

Table 5. Results of the regression model.

	Model 1		**Model 2**	
Coefficients	**Estimate**	**t value**	**Estimate**	**t value**
(Intercept)	0.187	67.056***	0.195	69.717***
HHI	0.035	15.696***	0.009	3.805***
Digital Orientation	0.073	2.537*	-1.065	-23.434***
DO_HHI	-	-	3.175	32.004***
Time to Grant	-0.007	-19.911***	-0.007	-18.898***
# Backward Citations	0.003	444.397***	0.003	443.773***
# IPC Subgroups	0.037	347.624***	0.037	347.572***
# Active Authorities	0.040	248.431***	0.040	248.186***
Dummy IPC A	-0.008	-5.43 ***	-0.010	-6.163***
Dummy IPC B	0.084	61.669***	0.084	61.998***
Dummy IPC C	-0.152	-86.279***	-0.147	-83.093***
Dummy IPC D	0.030	6.079***	0.031	6.286***
Dummy IPC E	0.123	44.280***	0.123	44.114***
Dummy IPC F	0.088	51.435***	0.090	52.590***
Dummy IPC H	0.040	30.582***	0.037	28.482***
Filing Year (Dummies)	Yes		Yes	
AIC	9,906,059		9,904,700	
N	3,782,972		3,782,972	
Note: *** and * indicate statistical significance at the 1% and 10%-level, respectively.				

Model 2 has a slightly lower AIC, Akaike Information Criterion, (9,904,700) than Model 1 (9,906,059), indicating a better fit (Akaike, 2011). For both models, all coefficients are highly significant with ($p < 2e-16$, indicated by ***), except for the dummy variable Filing Year 2001 (insignificant for both models) and digital orientation in Model 1 which is weakly significant ($p = 0.011$, indicated by *). Recognizing that our dependent variable technology relevance is calculated using the number of forward citations, we also calculated both models using the number of forward citations as an alternative dependent variable. While the results are similar, this additional analysis allowed us to assess the consistency of our findings across different specifications, thereby strengthening the validity of our conclusions.

Hypothesis 1 suggests that technological convergence, measured by HHI, has a positive association with patent value, which is calculated by technology relevance. In Model 1, our independent variable HHI has a highly significant positive effect on our dependent variable technology relevance (1% significance level). Accordingly, we find support for hypothesis 1. Simultaneously, our second independent variable digital orientation also has a significantly positive link with technology relevance, although to a weaker extent (10% significance level).

Hypothesis 2 suggests that the link between technological convergence and patent value is positively moderated by digital orientation. Thus, Model 2 includes variable DO_HHI, the interaction term of technological convergence (HHI) and digital orientation. The interaction variable shows a highly significant positive association with technology relevance. In parallel, the direct positive link of HHI on technology relevance is reduced but remains statistically significant, indicating that the interaction variable explains the link with technology relevance better compared to the formerly separate independent variables. Further, the direct link between digital orientation and technology relevance becomes significantly negative. Our calculations, using the number of forward citations as the dependent variable, lead to similar results as with our primary dependent variable technology relevance

In both models, Time to Grant is negatively associated with technology relevance, meaning that it takes less time for the patent family to be granted by the USPTO, the higher the technology relevance of that respective patent family is. Taking a look at the IPC section dummies, we see a significantly negative effect of IPC section C (Chemistry; Metallurgy) and IPC section A (Human Necessities). This indicates that patents associated with these IPC codes tend to be less valuable compared to our reference IPC section G (Physics).

6. Discussion

This study aims to provide an empirical answer to the question of how technological convergence is related to business value. Therefore, we derived two hypotheses which we empirically tested by calculating two separate regression models using more than 3.7 million patents. We find that technological convergence is positively associated with patent value, which represents business value. This link is positively moderated by the level of a patent's digital orientation. Subsequently, we first discuss the implications of our results. Second, we show the potential limitations of our study, followed by, third, highlighting avenues for future research.

6.1. Implications

Our theoretical implications are twofold. First, we show with Model 1 that a patent assigned to a heterogeneous set of technology classes is more valuable. The HHI, which represents technological convergence, has a significantly positive effect on our dependent variable technology relevance. In other terms, for the first time in IS research, we empirically confirm that technological convergence is positively linked to a patent's value. We argue that the ability to converge a wide range of technologies, as measured by IPC codes, lays the baseline for that patent to be cited by an increasing range of subsequent patents. With Model 1 we see that technological convergence exists regardless of the digital orientation of a patent. These findings are in line with Rosenberg (1963) who observed technological convergence in the 19th century, way before the introduction of digital technologies. While Rosenberg (1963) provided exemplary examples of technological convergence in the 20th century, we provide a novel way to measure technological convergence and show its effect across more than 3 million patents across time and industries in the 21st century. Thus, we trace the link between technical convergence and patent value across all granted patents (by the USPTO) filed between 2000 and 2018, resulting in a one-of-a-kind longitudinal study.

Second, we add to existing research by exploring how digital orientation influences the link between technological convergence and patent value. We do so by calculating the interaction term DO_HHI and integrating it in our Model 2. Our results show that digital orientation in combination with technological convergence has an even higher positive association with patent value than technological convergence or digital orientation individually. This finding is fortified by the lower AIC of Model 2, validating that the interaction term delivers a better explanation for patent value than its variables separately. While existing literature has conceptually argued that the increasing use of digital technologies may contribute to higher levels of convergence (Seo, 2017; Tilson et al., 2010), we are able to show the moderating effect of digital orientation on the link between technological convergence and patent value empirically. Moving beyond existing literature, we show that not digital orientation alone, but especially in combination with technological convergence is linked to a higher business value for companies. Our analysis shows that digital orientation turns out to be negatively linked to technology relevance when the interaction term DO_HHI is added, showing a dampening effect. This indicates that digital orientation contributes especially in coexistence with technological convergence to business value. Consequently, our analysis makes an important contribution to understanding technological convergence in the digital age. Simultaneously, technological convergence itself has a higher contribution to patent value than digital orientation. These results support that digital innovation often relies on the recombination of existing physical and digital components (Yoo et al., 2010). Thus, especially patents that – at least partially – rely on known technological components within their recombination are most valuable.

Our study also contributes to industry practices. Securing a patent requires filing an application with the respective patent office, which incurs costs for the applicant, such as labor effort or filing fees. By understanding what influences a patent's value, applicants can adjust their patent strategy by incorporating and promoting digital technologies, eventually increasing its patent value.

6.2. Limitations and avenues for future research

As with any research, this study holds various limitations. These limitations open several avenues for future research.

Firstly, our study only considers *technological* convergence. Yet, literature has also emphasized that the increasing use of digital technologies leads to a market or industry convergence (Seo, 2017; Tilson et al., 2010). To understand the complete spectrum of digital convergence as a socio-technical concept, we must consider not only technological convergence but also industry and market convergence. Thus, future research may incorporate industry data with patent data. Müller et al. (2022) use Standard Industrial Classification (SIC) codes to show that technological convergence increases over time to different levels and speeds, depending on the industry. These SIC codes can be used to assess our research model across specific industries

Secondly, we used patent value as a proxy for business value. We refer to the definition by Trajtenberg (1990). However, we acknowledge that this is only an approximate measure and cannot fully represent business value. For instance, some patents may not be used for commercial purposes. Future research could consider incorporating other factors to more comprehensively capture business value.

Thirdly, while we included several control variables such as the time to grant, number of backward citations, IPC subclasses, IPC section dummies, and filing years, there might be additional effects influencing a patent's value. This includes for example the amount of research and development expenditures by the patent applicant (Guo et al., 2023) or its ratio to published patents (Geerts et al., 2018). In addition, we note several interesting effects concerning the time it takes for a patent to be granted. In both our models, time to grant is significantly negatively linked to our dependent variable technology relevance. Being a time measure, this means that it takes less time for a patent to be granted by the USPTO the more valuable it is. This could indicate that a valuable patent might incorporate additional factors that are recognized by the patent office thus reducing the process at the patent office. These additional factors could be explored by future research.

Fourthly, our study focuses on patent families which have at least one family member granted in the United States (US), omitting inventions from other regions in the world, e.g. inventions only protected in Asia or Europe. While many related research studies also build on USPTO data (Funk & Owen-Smith, 2017; Choi et al., 2021; Lahiri, 2010), there are examples of extending the scope of granted patents to Europe or Japan (Baudry & Dumont, 2006; Nikzad, 2014). We already reduced this US-centric effect by using patent data on the family level, since this level includes metadata from other jurisdictions, too (Ernst & Omland, 2011). However, future research may also compare the link of technological convergence and patent value between European to US patents or even focus on triadic patent families, i.e., on patents that were granted in coexistence by the following jurisdictions: by the European Patent Office, the Japanese Patent Office and by the USPTO (Baudry & Dumont, 2006).

Lastly, we stretched the application range of the measure digital orientation which was originally calculated using financial reports (Drechsler et al., 2023). In the paper, we applied this measure to the patents' abstracts, but not the full text of patents, which may offer a more comprehensive description of a patent. By demonstrating that this measure can also be utilized for technical documents, such as patents, we open up opportunities to combine financial and patent data in future research.

7. Conclusion

In this paper, we take a closer look at the relationship between technological convergence and patent value over time. Our analysis of a longitudinal patent data set reaching from 2000 to 2018 and including 3,782,973 patent families enables us to make two key contributions: First, we show that technological convergence has a significantly positive association with patent value and, second, this link is significantly moderated by the degree of a patent's digital orientation. Thereby, we show how our results confirm existing theories and observations on technological convergence and highlight how our study extends existing research on convergence by providing empirical findings based on a large dataset.

8. References

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