The Interplay Between Technology and Pre-Industry Convergence: An Analysis in the Technology Field of Smart Mobility

Huseyin Caferoglu, Dag Elsner, and Martin G. Moehrle

Abstract—**Previous studies examine convergence by focusing on different individual levels such as the science, technology, market, and industry level. However, little is known about the concrete interaction between these levels. To fill this gap, this article deals with the transition between technology convergence and industry convergence at a very early stage (which we will be referring to as pre-industry convergence). We combine semantic and bibliographic analyses in a four-step approach in order to jointly measure both convergence levels by means of patents. We apply our method to the technology field of smart mobility as a promising test bed. Our results show that technology and pre-industry convergence occur simultaneously several times. However, we identify four conditions under which there is no connection at all or a time-lagged connection between both convergence levels. In particular, the connection is missing, if entering a technology field requires deep and specialized technical know-how or if there are high market entry barriers due to incumbent companies that started patenting in a technology field at an early stage. Additionally, if incumbent companies are small and specialized, they do not drive pre-industry convergence, as they do not enter distant markets. In general, it is more difficult for companies from distant industries to enter convergence processes in infrastructure-related technologies than in product-related technologies. Furthermore, there is a time-lagged connection, if pre-industry convergence follows technology convergence with a delay. This occurs if technology convergence is initially driven by application-oriented companies that exploit these technologies for their niche markets.**

Index Terms—**Bibliographic analysis, industry convergence, semantic patent analysis, smart mobility, technology convergence.**

I. Introduction

IN TODAY'S world, convergence is a widespread phenomenon that challenges companies from many industries, including opportunities to enter new markets as well as the threat of losing market shares. Convergence has many facets; it may take place on a science, technology, market, or industry level. Some examples of market convergence are products like functional foods, which combine agricultural and pharmaceutical knowledge [1], [2], intelligent buildings, which combine knowledge from construction, computer science, and the energy sector [3], and—as flagship-example—the smartphone. The smartphone involves influences from various technologies due to unifying their functions, e.g., mobile phone, digital camera, computer, and GPS [2], [4]. By doing so, it dramatically disrupted the status-quo: it established a completely novel market, whereas the traditional mobile phone and the mainstream camera suffered a dramatic loss in lost market shares.

Occasionally, market convergence can lead to convergence on an industry level. In such cases, the emergence of a new industry segment may substitute its antecedents, leading to an industry shakeout. For example, Nokia was a leading mobile phone manufacturer that was bought out by Microsoft in 2013 [5]. Shortly after the bought out, its one billion-dollar-worth core competencies became obsolete due to industry convergence. Thus, convergence—especially on the industry level—creates opportunities for new market entrants while posing a threat to incumbent companies, requiring them to constantly monitor their technological environment for early warning signals.

Having given some examples of convergence on the market and industry levels, we move on to a definition of the term as such. Convergence can be regarded as a sequential process comprising four levels, namely those of science, technology, market, and industry [1]. While science convergence addresses the merging of distinct research areas, technology convergence deals with the blurring of boundaries between technologies. Market convergence (following either science or technology convergence) manifests itself in new product-market combinations. In this context, industry convergence constitutes the final level "*evolving when scientific disciplines and technologies and/or markets have converged*" [1, p. 386]. Previous studies propose multiple indicators to measure convergence on each of the introduced levels. However, most of these indicators focus on the convergence of science, technology, and market, and manage to measure it at an early stage. Early industry convergence, on the other hand, is only measured on the basis of one single indicator: M&A data [5].

Industry convergence can generally be defined as the "*blurring of boundaries between industry*" [2, p. 273], "*fusion of firms*" [1, p. 387] or a stage in which "*firms from previously distinct industries […] suddenly become competitors*" [3, p. 728].

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Obviously, industry convergence is a complex concept. To deal with this, Sick *et al.* [5] start from the assumption that industry convergence will cause the core competencies of incumbents to become obsolete and force them to acquire new competencies in order to survive the technological change. Consequently, the authors argue that industry convergence will lead to different types of collaboration between distant companies, with the aim of filling competence gaps.

Previous studies examine convergence by focusing on different convergence levels individually. Doing so, they miss the opportunity to gain new practical and theoretical insights from the interplay between these levels. For instance, although technology convergence represents a prestage of industry convergence, it is still unclear how both levels concretely interact, and under what circumstances technology convergence may lead to industry convergence. Knowledge about this interplay is crucial, as it may help to anticipate industry convergence at an early stage. Consequently, our current study is based on a central research question: In what way do pre-industry convergence (i.e., industry convergence at a very early stage) and technology convergence interact with each other?

In order to answer this question, we introduce the operationalization of pre-industry convergence and propose a new approach to measuring it. Especially, in addition to the idea of collaboration, we argue that pre-industry convergence takes place when technologically distant companies start patenting in a technology field that is not part of their usual technological competence. Thus, we focus on patent data, as it enables a joint measurement of technology as well as pre-industry convergence. Although we use the same basic data for both purposes, we focus on different parts of the patents, respectively, utilizing assignee data for pre-industry convergence, but performing semantic similarity measurement based on textual parts (title, abstract, and claims) for technology convergence.

This article is organized as follows. In Section II, we discuss the theoretical background. In Section III, we retrieve our dataset related to smart mobility, which comprises four technologies, namely the traffic management system, autonomous driving, electric vehicle, and (battery) charging infrastructure. In Section IV, we present our patent analysis approach based on semantic anchor points to measure technology convergence, and bibliographic assignee analysis to identify pre-industry convergence. In Section V, we present our results and examine the interplay between both convergence levels. Finally, Section VI concludes this article. In terms of theoretical implications, we show that pre-industry convergence often occurs simultaneously with technology convergence, but under specific conditions there is either no connection at all or a time-lagged connection. As a managerial implication, we provide a method that enables analysts to measure two types of convergence at an early stage based on the same source. Hence, using our method may provide them with a lead-time advantage to prepare for upcoming changes.

II. Theoretical Background

In the following, we establish our theoretical framework. For this purpose, we proceed in three steps. First, we introduce the concept of convergence in general and outline its importance for technology management studies. Second, we discuss the sequential model of convergence and already known indicators. Third, we discuss the operationalization of pre-industry convergence.

Convergence describes a process in which at least one of several previously unconnected objects—such as different scientific areas, technologies, markets, or industries—moves toward another object. This may also involve more than a single one-directional movement, e.g., two objects moving toward each other. In result of a convergence process, established boundaries fade and merge into a new object. As Curran and Leker [4] propose, this merging may be driven by at least one object. More specifically, in case of a one-way convergence only one object leaves its spot and moves into the direction of the second object. In contrast, a two-way (or more-way) convergence occurs, if all objects move toward a new spot [6]. In either case, the convergence may be of a complementary (i.e., the new object complements its antecedents) or substitutive (i.e., the new object replaces its antecedents) nature [1]. Consequently, convergence creates an opportunity for new entrants to a market while posing a threat to incumbent companies whose core competence no longer represents any competitive advantage; rather, they now have a competence gap and face the reality of competing against companies from previously distant industries with different competencies [2], [5]. For this reason, it is of vital importance for a company to recognize convergence at an early stage to obtain a lead-time advantage and prepare for the change.

Previous studies have established convergence to be a sequential process comprising four levels, namely those of science, technology, market, and industry [1]. The first level of convergence begins when a decrease in the distance between two distinct fields of science becomes perceivable in citations or collaborations between both research fields, which can be identified through citation analysis of scientific publications. Second, the effect moves on to the technology level, where previously distant technological knowledge is combined to solve a certain technical problem. This level of convergence is usually analyzed by means of patent data [6]. On the third level, an overlap between markets can be observed, represented by new product-market combinations [1]. Finally, on the fourth level, a convergence of industries takes place, in which new industries emerge where *"firms from previously distinct industries [...] become competitors*" [3, p. 728].

Ample work has been done to analyze convergence on these different levels. There are several approaches that attempt to measure convergence at an early stage. For instance, Jeong *et al.* [7] use cocitations of scientific publications to identify early signals of science convergence. Eilers *et al.* [6] measure technology convergence based on patent data by means of semantic anchor points. Aaldering *et al.* [8] apply a machine-learning algorithm to M&A data and predict future cross-market M&A transactions, which they use as a proxy for market convergence.

However, there is a lack of work, which analyzes the interplay between different levels of convergence. In particular, the interplay between technology convergence and industry convergence is of interest, as an existing study uses technology convergence as an indicator of potential industry convergence [9]. Our central research question takes this aspect into focus: In what way does industry convergence concretely interact with technology convergence?

To answer this question, we focus on the concept of pre-industry convergence, which enhances the existing concept of industry convergence. It represents a stage in which weak signals of companies' movements can be perceived. More specifically, signals of pre-industry convergence can occur when companies from distant industries enter a specific technology field. This entrance may take place with or without cooperation between different firms. In the example of smartphones, Apple Inc., a company that had not been active in the telecommunication industry previously, was one of the convergence drivers and started developing smartphone technology before the final industry convergence occurred.

The concept of pre-industry convergence expands the existing concept of industry convergence by consideration of an additional stage. In prior work, Sick *et al.* [5] propose a cooperation framework for the assessment of industry convergence. For this purpose, the authors define six subtypes of industry convergence based on two criteria, namely the type of industry convergence (complementary or substitutive) and stages of industry convergence (early, medium, or late). The authors assume that industry convergence takes place when companies try to close their competence gaps by means of collaboration; consequently, the authors propose indicators of collaboration for each subtype. The concept of pre-industry convergence explains a preceding stage, in which cooperation is not necessarily taking place. Therefore, it can be seen as the stage prior to early industry convergence according to the framework proposed by Sick *et al.* [5], without neglecting the fact that there may be overlaps between these two stages. Some companies may actually do both—cooperate *and* enter a new technology field. In such cases, pre-industry convergence and early industry convergence do overlap. However, other companies might enter a new technology field without cooperation. In such cases, pre-industry convergence is separated from early industry convergence.

When it comes to selecting an appropriate data source that offers access to early signals,[1] we suggest using patent data. Often, companies protect their knowledge by means of this legal instrument for safety reasons long before entering a new market, even waiting for a granting decision. Furthermore, the advantage of this kind of data lies in the fact that technology and pre-industry convergence can be measured simultaneously, as patents do not only reveal technical knowledge but also provide information regarding the assignees, which makes them suitable for the study of pre-industry convergence.

In summary: Our theoretical framework adopts the sequential process of convergence and expands it by integrating the idea of pre-industry convergence. Pre-industry convergence as a concept adds another stage to the prior definition of industry convergence. While blurring boundaries caused by industry convergence point to a new industry segment, in cases of pre-industry convergence we expect to observe individual companies making very early entries into distant technology fields as an expression of their convergence efforts.

III. Data

This section addresses our data selection and retrieval process in terms of three aspects. First, we provide an introduction to smart mobility as our case technology. Second, we describe our data retrieval process. Third, we evaluate the quality of our data and prepare it for further analysis.

For our analysis, we select the case example of smart mobility. Smart mobility aims to rethink mobility systems in a modern, more sustainable, safe, and innovative way by utilizing information and communication technology (ICT) [10, p. 12]. Our decision is motivated by three reasons. First, smart mobility is a relevant and current field of technology, addressing various problems of today's societies, such as climate change, urban air pollution, and congested transport systems. Second, smart mobility is a young field of technology in which no dominant design has yet emerged. Considering both reasons in combination, a high interest in developing smart mobility solutions by companies from diverse technology backgrounds can be expected. This interest is reflected by a high number of market entrants that are aiming to gain a first-mover advantage by establishing their solutions. Third, smart mobility appears suitable for our examination because we see that several players from big industries—such as the automotive, energy, and ICT sectors—have to work together when it comes to real use cases. There are many examples in which different technologies and industries are involved, for instance the "ecosystem" of Tesla, Inc. (semiautonomous electric vehicles, charging infrastructure and decentralized energy generation and storage) or VW's MOIA ride-pooling service (app-based mobility service, utilizing electric vehicles and sharing concepts). As we can already see indications of convergence in this context, we assume that smart mobility is suitable for examining convergence on the technology as well as the pre-industry level.

Utilizing the technology complex to delineate a field of technology as suggested by Geschka and Hahnenwald [11], we divide the technology field of smart mobility into four subtechnologies, namely traffic management system, electric vehicle, autonomous driving, and charging infrastructure. By traffic management system, we understand the efficient and safe utilization of existing transportation infrastructure. This includes devices such as static and dynamic traffic signs, traffic lights, algorithms that control these dynamic devices, and the interaction between vehicles [12]. Often, the term electric vehicles merely refers to electric cars. We, however, use it in a broader sense, including all kinds of vehicles that are propelled by an electric engine and battery. In our understanding, autonomous driving technologies comprise all technological devices, means, and algorithms that reduce driver actions in controlling a vehicle. Charging infrastructure is required for charging the batteries of electric vehicles. This term mainly refers to charging stations for

[1]The patent office discloses patent applications at the latest 18 months after the application date. 18 months seem to be a long timeframe; nevertheless, no other data source provides better documented as well as earlier information about technologies.

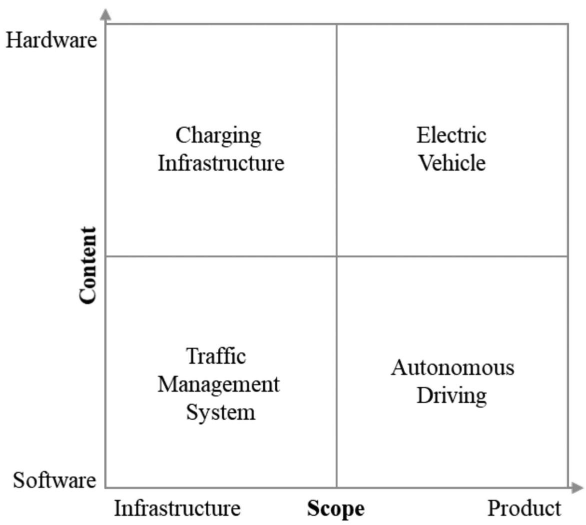

Fig. 1. Characteristics of subtechnologies in terms of scope and content. Source: Authors.

electric cars, but given our broad definition of electric vehicles, it may also refer to charging devices for any other electric vehicle.

All four subtechnologies are related to each other under the roof of smart mobility. To gain an understanding of their relationship, we suggest considering two different poles. The first pole is formed by a clear interface definition, leaving the connected technologies behind the interface unaffected. The second pole is characterized by various overlaps between the technologies at hand, far beyond the interface. We expect to see different convergence values, based on the proximity between pairwise technology combinations and the two poles.

A special characteristic of our data lies in the diversity of the individual subtechnologies, which enables us to perform a differentiated analysis. This diversity can be summarized according to two dimensions, namely related to the content and to the scope of the technologies. First, our data differ in terms of scope between infrastructure-related technologies and product-related technologies. Second, with regard to content, our dataset includes hardware-driven as well as software-driven technologies. As Fig. 1 shows, each of our technology fields can be assigned to a distinct combination.

Following previous convergence studies, we select patents as a data source for the following three reasons [6], [13]–[16]. First, patents form the world's largest data source of technical knowledge that has not been published anywhere else [17], [18]. Second, patents have a standardized structure (e.g., title, abstract, claims) as ensured by the patent examiner during the examination process and are thus preferable for computer-aided analysis [18], [19]. Third, apart from technical and legal aspects, patents also provide information related to the assignees, which makes them suitable for the study of pre-industry convergence.

To retrieve patents related to our four subtechnologies, we perform a patent search in the USPTO PatFT database (see Table I). An important aspect of this step is the correct delineation of the respective subtechnologies. For this purpose, we generate search strings by combining classification and keyword searches as suggested by Alberts *et al.* [18] and Clarke [20]. This step is essential, since it determines the quality of the input data, which in turn affects the overall method [19], [21], [22]. To be more precise: If the delineation of a technology is too narrow, it is likely that only a subset of the relevant hits will appear. Consequently, the analysis will not be representational for the technology. If, on the other hand, the delimitation is too relaxed, irrelevant patents will appear and thus bias our analysis. As a result of our search strings, we retrieve 1709 patents related to traffic management systems, 1357 patents related to autonomous driving, 3087 patents addressing electric vehicles, and 321 patents addressing charging infrastructure.

In order to monitor the quality of our search strings, we pursue the approach by Egghe [22] to measure precision and recall. Precision represents the percentage of relevant patents in a search result. In our case, we pick a random sample[2] of patents for each technology and manually examine their relevance. To calculate the precision for each technology, we divide the number of relevant patents in our sample by the sample size.[2] Multiplying the precision value by the number of retrieved patents, we establish the total of relevant patents according to our search strings. In addition to this, recall focuses on the fraction of relevant patents from the entire database that have been identified by the search string. For this purpose, we follow the relax-and-sample approach by Moehrle [21] and proceed in three steps. First, we relax our search strings for each technology by using a more abstract classification level. Second, in analogy to precision, we calculate the total of relevant patents in the relaxed search, based on a sample[1] of patents. Third, we estimate the recall by dividing the number of relevant patents from the original search by the number of relevant patents from the relaxed search.

As presented in Table II, our dataset is characterized by a high precision and a relatively low recall.[3] This is advantageous because it means that almost all patents from the search are relevant and that there only is low noise in the data. At the same time, we assume that other relevant patents that could not be found by means of our search string are rather similar to those patents we did find. Although we checked this manually by comparing several examples, we have to accept that there may be a bias.

In the final step, we divide our data into four timeframes. This step is crucial for our analysis since convergence is a dynamic process and needs to be evaluated over time. Thus, we decide to use four ten-year timeframes, ranging from 1979 to 2018. Fig. 2 shows the distribution of granted patents per timeframe. Due to the fact that smart mobility is a young and growing field of technology, the majority of respective patents occur in the

[2]In analogy to Passing [23], we determine the minimum sample size required for each technology separately (for details and settings, see [23, p. 49]). The sample sizes for determining the precision are 50 (traffic management system), 49 (autonomous driving), 43 (electric vehicle), and 49 (charging infrastructure). The sample sizes for determining the recall are 68 (traffic management system), 44 (autonomous driving), 57 (electric vehicle), and 51 (charging infrastructure).

[3]Usually, there is a tradeoff between precision and recall in patent searches, given a specific effort (see [22]).

TABLE I
SEARCH STRINGS FOR EACH SUBTECHNOLOGY OF SMART MOBILITY

Technology	Search String	Patent Count
Traffic Management System	((ICL/G08G$ not ICL/G08G3/$ not ICL/G08G5/$ not CPC/G08G3/$ not CPC/G08G5/$) or (CPC/G08G$ not ICL/G08G3/$ not ICL/G08G5/$ not CPC/G08G3/$ not CPC/G08G5/$)) and (SPEC/traffic$ and SPEC/vehic$ and SPEC/control$) and (ABST/vehic$ and ABST/traffic$) and ISD/19760101->20190131	1,709
Autonomous Driving	(ABST/autonomous or ABST/"self-driving" or ABST/"self driving") and (ABST/vehicle or ABST/automobile) not (ABST/rail$ or ABST/air$ or ABST/aer$ or ABST/marin$ or ABST/sea$ or ABST/ocean or ABST/underwater) not (TTL/rail$ or TTL/air$ or TTL/aer$ or TTL/marin$ or TTL/sea$ or TTL/ocean or TTL/underwater) and ISD/19760101->20190131	1,357
Electric Vehicle	ABST/"electric vehicle" and (CPCL/B60L or CPCL/B60K or CPCL/B60W or CPCL/Y02T) and ISD/19760101->20190131	3,087
Charging Infrastructure	(CPCL/B60L) and (ABST/charg$ or ABST/recharg$) and ABST/station and ABST/electric$ and (ABST/vehic$ or ABST/autom$ or ABST/car or ABST/motorcar) and ISD/19760101->20190131	321

Source: Authors

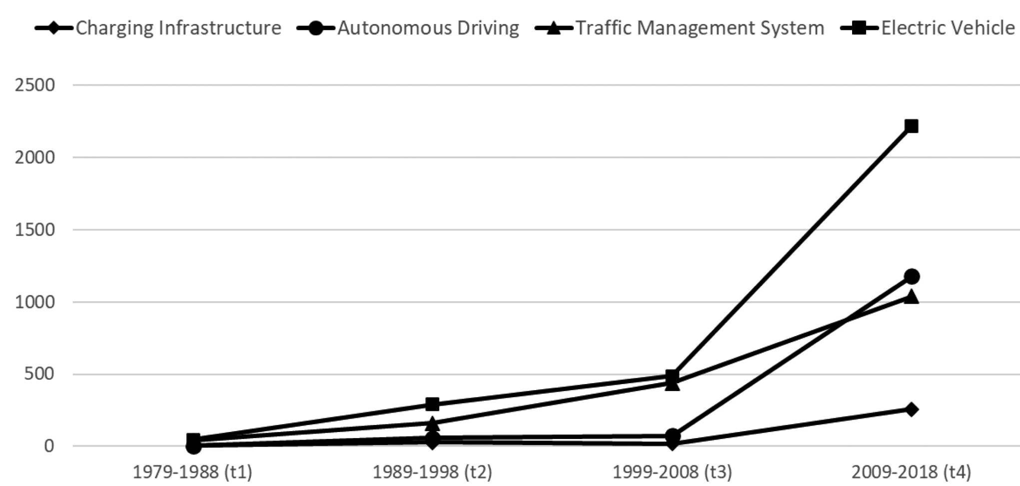

Fig. 2. Retrieved granted patents for each subtechnology of smart mobility per timeframe, organized by application date. Source: Authors.

later timeframes. More specifically, the first timeframe contains a particularly low proportion of patents, which is why we do not take it into consideration for our analyses. Consequently, all analyses in this study refer to timeframes 2–4.

IV. Method

In the following, we present our methodical approach to measuring technology and pre-industry convergence. Prior to our four-step approach, we provide an overview of already existing approaches to measuring technology convergence and industry convergence. Our methodical approach is based on the following three considerations. First, we intend to use the same type of data for both examined levels of convergence to avoid a data source bias. Second, we apply the same dataset to both levels of convergence to include the same systematic errors (if any). Third, we aspire to use recent data in order to mirror the situation in companies, which require timely information. Consequently, our approach comprises four steps (see Fig. 3), namely, developing semantic anchor points, measuring semantic similarity, analyzing assignees, and estimating convergence. While the first two steps focus on technology convergence by means of semantic similarity measurement between patents, the third step examines pre-industry convergence by means of assignee analysis. The final step is related to both levels of convergence.

There are several approaches to measuring technology convergence by means of patent data. For instance, assuming that the merging of two distinct technologies will be reflected in patent

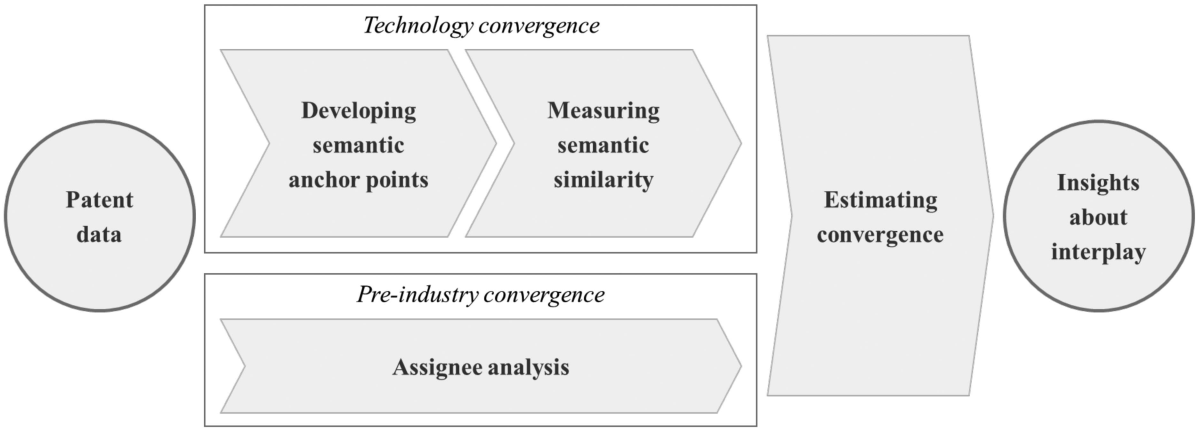

Fig. 3. Methodical approach in four steps. Source: Authors.

TABLE II
VALIDATION OF PATENT SETS

Technology	Precision	Recall
Traffic Management System	0.81	0.21
Autonomous Driving	0.80	0.11
Electric Vehicle	0.84	0.07
Charging Infrastructure	0.78	0.15

Source: Authors

classifications, one line of approach utilizes coclassification techniques [4], [24]. According to this, a convergence occurs when patents are coclassified in two (previously) unconnected patent classes. Another approach analyzes backward citation data and uses knowledge flow from distant technologies as an indication of convergence [25], [26]. However, both approaches are limited, as they are subject to time lags. In particular, information related to backward citations and classifications is not listed completely when a patent is disclosed, instead it only becomes fully available once the patent has been granted. To overcome this obstacle, we decide to use a semantic measurement approach in accordance with [13], as technical information embedded in the textual content directly becomes available at the disclosure of a patent.

With regard to pre-industry convergence, we are aware of the approach presented by Sick *et al.* [5] for the identification of early industry convergence. The authors assume that companies that are interested in closing their competence gaps caused by convergence may enter into collaborations with companies from distant industries. Thus, the authors suggest regarding collaborations between companies as a proxy for early industry convergence, which they therefore measure by use of news sources. However, as pre-industry convergence represents an earlier stage, its measurement should take account of companies that enter a distant technology field without collaboration. This may, for instance, be due to the circumstance that they do not have any competence gap or that they fill existing gaps by hiring new personnel. In line with these thoughts, we argue that patents are a suitable information source for measuring this phenomenon.

A. Developing Semantic Anchor Points

The aim of the first step is to generate semantic anchor points, i.e., lists of bigrams that are characteristic for a technology; a bigram being a combination of two independent terms that are located close to each other in a text document. Since technologies, and consequently their textual content, are subject to change over time, we develop four semantic anchor points for each examined timeframe (timeframes 2–4), representative of each technology within our chosen technology field of smart mobility. In order to achieve this, we proceed according to three substeps, namely: selection of patent parts, generation of term-document matrices, and relevance assessment.

First, following previous work on semantic patent analysis, we decide to focus on the title, abstract, and claim parts of patents [6], [15]. These parts mainly address the technical aspects of an invention, which are essential for characterizing the technologies at hand [13], [27]–[29]. Thus, by excluding all other parts, such as descriptions, which include information related to the invention's state of the art, we reduce the noise.

Second, we generate term-document matrices. For this purpose, we first preprocess the textual content with the aid of the PatVisor.[4] In particular, we clean and unify the text by deleting punctuations, numbers, stop words, symbols, and patent-specific words, and by applying a lemmatizer to reduce every word to its root. Additionally, in accordance with [30], we extract bigrams based on a window size of 4, in which the window size represents our understanding of proximity between terms. After manual inspection, we set the minimal word length to 3, so that terms comprised of less than three characters are eliminated. Bigrams we extract are, for instance, autonomous control, signal traffic, and charge station.

[4]The software PatVisor is an open software package, which was developed by the Institute of Project Management and Innovation at the University of Bremen for the purpose of patent analysis. [Online]. Available: https://patvisor.ipmi.de/

Third, we perform a relevance assessment to identify bigrams that are characteristic for a given technology. In this context, two questions need to be answered: *How many bigrams should a semantic anchor point contain?* And: *Which bigrams should we select for a semantic anchor point?* To answer these questions, we refer to the information gain (IG) that we calculate for each term document matrix. The IG measures the information content of a term relative to a particular set of documents and ranges between 0 and 1 for each term [23]. Consequently, bigrams with a high IG value are particularly relevant and characteristic for a given pool of patents. To establish the optimal anchor point size, we follow [23] and apply a heuristic: We divide the value range of the IG into ten intervals [0.1, 0.2, … 1]. For each interval, we create an anchor point candidate consisting of bigrams with an IG value bigger than the interval value. Doing so, we create ten anchor point candidates for each technology in each timeframe. For each semantic anchor point candidate, the similarity mean (for setting see next step) to its own patent set in the regarded timeframe is measured. Our final anchor point is the one with the highest similarity mean in relation to its own patent set.

B. Measuring Semantic Similarity

The aim of the second step is to calculate the similarity between semantic anchor points and patent sets. This step is carried out separately for each timeframe. To achieve this, two design decisions have to be made regarding the similarity measurement [31]. First, we have to define the linkage type, i.e., the question of how to count links between a patent and a semantic anchor point. In this study, we follow [23] and use reduced linkage as the linkage type. Doing so, we emphasize that the similarity between patent and anchor point increases with the distance between bigrams in both sets, regardless of their term frequency [31]. Second, we have to decide on the similarity coefficients, i.e., the formula that refers to the linkage counts to calculate the similarity. We use the Jaccard similarity coefficient, which is calculated as the "*overlap […] divided by the remaining non-overlapping concepts*" [31, p. 110]. As a result of this step, we receive a similarity matrix for each timeframe, which contains the similarities between patent sets and semantic anchor points.

C. Analyzing Assignees

Semantic measurement helps understand technology convergence. With regard to pre-industry convergence, we use another piece of information from patents: assignee(s), i.e., the names of companies or inventors who strive to protect the disclosed invention. For the purpose of our analysis, we focus on patents assigned by companies only, excluding individual inventors. Our basic idea is to classify these companies in five categories, depending on whether the assignee's technology field is related to any technology field of smart mobility or to a distant technology field. For this purpose, we additionally search for all patents belonging to the assignee. We define the assignee's core competency based on the frequency of patent classes to which these patents have been assigned. More specifically, we proceed in three substeps. First, we represent each technology in the field of smart mobility by means of cooperative patent classification (CPC) classes. Second, we determine the core technology fields of all assignees by means of CPC. Third, we compare both lists to identify smart mobility related and smart mobility distant assignees.

In the first substep, we determine the CPC classes that represent the four technologies of smart mobility (see Table III). For this purpose, we perform a subclass CPC analysis based on the search strings defined in the data section. Doing so, we identify the CPC classes G08G and G01C as representative for the traffic management system, G05D and B60W for autonomous driving, B60L and B60K for electric vehicle, and B60L for charging infrastructure. For our analysis, it is important that there is no CPC overlap between the technologies at hand, as otherwise a company would be assigned to multiple technology fields and thus bias our analysis. To avoid this kind of bias, we dive into a more detailed subgroup CPC analysis for the case of B60L. In particular, we retrieve the CPC classes on a subgroup level for all assignees with the core technology field B60L (see next substep), then categorize them manually to either charging infrastructure technology or electric vehicle technology, based on the CPC descriptions (see Table IV).

In the second substep, we identify the core technology field of each assignee. We start by carrying out a patent search based on all assignee names and retrieve the metadata of all assignee's patent portfolios. Next, based on this metadata, we harmonize assignee names by converting them to lower case only, deleting punctuations, deleting spaces at the beginning and the end of all names, and deleting legal forms (such as corporation or incorporated). Doing so, we achieve to unify assignee names that occur in different variants according to legal forms. Since in our analysis we consider companies and their subsidiaries separately, we do not standardize every assignee name. Thus, we accept the possible error that in rare cases company names may appear twice due to spelling mistakes. We consider this error to be systematic, as it probably impacts all technologies in the same way. Finally, for each assignee, we select the most frequent first CPC subclass as a proxy for the core technology field. Since B60L is an overlapping CPC, we use the CPC subgroup level as a proxy.

In the third substep, we compare both lists and check whether assignees are related to any of the smart mobility technologies. We define an assignee as related to one of the four technologies if its core CPC class is equivalent to a technology's CPC. Doing so, we categorize all assignees into the following five groups:

1) traffic management system related;
2) autonomous driving related;
3) electric vehicle related;
4) charging infrastructure related;
5) distant from smart mobility.

D. Estimating Convergence

The final step estimates convergence on the technology as well as the pre-industry level. In both cases, we have to perform an aggregation of the data on the technology field level and define a threshold value to quantify convergence.

TABLE III
OVERVIEW AND DESCRIPTION OF CPCS USED TO DELINEATE THE FOUR SMART MOBILITY TECHNOLOGIES

Technology	CPC	CPC Description
Traffic Management System	G08G	Traffic control systems
	G01C	Measuring distances, levels or bearings; surveying; navigation; gyroscopic instruments; photogrammetry or videogrammetry
Autonomous Driving	G05D	Systems for controlling or regulating non-electric variables
	B60W	Conjoint control of vehicle sub-units of different type or different function; control systems specially adapted for hybrid vehicles; road vehicle drive control systems for purposes not related to the control of a particular sub-unit
Electric Vehicle	B60L	Propulsion of electrically-propelled vehicles
	B60K	Arrangement or mounting of propulsion units or of transmissions in vehicles; arrangement or mounting of plural diverse prime-movers in vehicles; auxiliary drives for vehicles; instrumentation or dashboards for vehicles; arrangements in connection with cooling, air intake, gas exhaust or fuel supply of propulsion units in vehicles
Charging Infrastructure	B60L	Propulsion of electrically-propelled vehicles

Source: USPTO

TABLE IV
SUBGROUP CPCS OF B60L SUBDIVIDED TO CHARGING INFRASTRUCTURE OR ELECTRIC VEHICLE AFTER MANUAL EXAMINATION

Technology	**Subgroup CPC**
Charging Infrastructure	B60L 11/1812, B60L 11/1818, B60L 11/184, B60L 11/1844, B60L 11/1846, B60L 11/1848, B60L 11/185, B60L 5/005, B60L 5/28, B60L 5/36, B60L 53/00, B60L 53/12, B60L 53/122, B60L 53/126, B60L 53/14, B60L 53/18, B60L 53/30, B60L 53/305, B60L 53/34, B60L 53/37, B60L 53/50, B60L 53/51, B60L 53/53, B60L 53/60, B60L 53/62, B60L 53/63, B60L 53/64, B60L 53/66, B60L 53/67, B60L 53/68, B60L 53/80, B60L 9/00, B60L 9/22, B60L 9/28, B60L 53/11, B60L 5/40
Electric Vehicle	B60L 1/00, B60L 1/003, B60L 1/006, B60L 13/10, B60L 15/007, B60L 15/20, B60L 15/2009, B60L 15/2018, B60L 15/2045, B60L 15/2063, B60L 15/2081, B60L 15/32, B60L 3/00, B60L 3/0015, B60L 3/0046, B60L 3/0053, B60L 3/0061, B60L 3/0069, B60L 3/0092, B60L 3/04, B60L 3/12, B60L 50/40, B60L 50/51, B60L 50/52, B60L 50/66, B60L 58/12, B60L 58/13, B60L 58/22, B60L 58/24, B60L 58/26, B60L 58/27, B60L 7/006, B60L 7/12, B60L 7/14, B60L 8/00, B60L 8/006, B60L 50/60

The lists do not include all subgroups of B60L, but are restricted to classes in which the assignees have patented. Source: Authors

In order to reveal technology convergence, we use the similarity matrices as input, which contain the values of similarity between patent sets and the semantic anchor points of a timeframe. We start by grouping the patents according to their technology fields. Next, for each technology field, we calculate the average similarity between the anchor point of the technology and grouped patents of the remaining technologies. For instance, in the case of the traffic management system, we calculate the average similarity between the patents for autonomous driving, electric vehicles, and charging infrastructure on the one hand, and the anchor point of the traffic management system on the other. We repeat this step for each anchor point in each timeframe.

Threshold values are useful for determining whether there is any convergence between technologies. We are aware that the definition of such threshold values is somewhat arbitrary. However, as by manual inspection we find a multitude of converging patents that possess a comparatively high similarity value and only a few with a low similarity value, we argue that this kind of threshold value is useful, even if its position may be debatable. For our case, we define two threshold values and related ranges, namely 0.015–0.024 for weak or equal, and greater than 0.025 for strong technology convergence, in analogy with [6]. Consequently, if the average similarity between the patents of traffic management system and the anchor point of electric vehicle exceeds the threshold value of 0.015, we consider

TABLE V
ASSESSMENT OF TECHNOLOGY CONVERGENCE

Anchor point: AD		Timeframe t2	t3	t4
Patent set	AD	**0.097**	**0.038**	**0.050**
	EV	0.013	0.015	0.016
	CI	0.008	0.009	0.019
	TMS	0.023	0.025	0.037

Anchor point: EV		Timeframe t2	t3	t4
Patent set	AD	0.006	0.019	0.016
	EV	**0.039**	**0.046**	**0.035**
	CI	0.020	0.010	0.027
	TMS	0.013	0.012	0.014

Anchor point: CI		Timeframe t2	t3	t4
Patent set	AD	0.007	0.024	0.019
	EV	0.037	0.020	0.031
	CI	**0.098**	**0.103**	**0.043**
	TMS	0.014	0.021	0.018

Anchor point: TMS		Timeframe t2	t3	t4
Patent set	AD	0.010	0.028	0.033
	EV	0.013	0.011	0.012
	CI	0.007	0.010	0.016
	TMS	**0.040**	**0.041**	**0.042**

Presented are average similarity values between semantic anchor points and patent sets over timeframes. The values in bold type indicate the similarity value of a semantic anchor point and its own patent set.

TABLE VI
ASSESSMENT OF PRE-INDUSTRY CONVERGENCE

Technology: AD		Timeframe t2	t3	t4
Assingee`s background	AD	**0.085**	**0.017**	**0.159**
	EV	0.000	0.042	0.008
	CI	0.000	0.008	0.010
	TMS	0.028	0.136	0.068

Technology: EV		Timeframe t2	t3	t4
Assingee`s background	AD	0.012	0.042	0.026
	EV	**0.046**	**0.042**	**0.061**
	CI	0.000	0.008	0.084
	TMS	0.000	0.000	0.004

Technology: CI		Timeframe t2	t3	t4
Assingee`s background	AD	0.000	0.000	0.009
	EV	0.208	0.154	0.057
	CI	**0.000**	**0.000**	**0.256**
	TMS	0.000	0.000	0.013

Technology: TMS		Timeframe t2	t3	t4
Assingee`s background	AD	0.000	0.010	0.037
	EV	0.018	0.010	0.003
	CI	0.000	0.000	0.004
	TMS	**0.266**	**0.267**	**0.219**

Presented are fractions of patents that are assigned by companies related to one of four technology fields of smart mobility over timeframes. The values in bold indicate the fraction of patents in a field, which is assigned to companies of this field.

this an indication of a weak one-way technology convergence from traffic management system to electric vehicle. If this phenomenon is also observable in reverse, we speak of a weak two-way technology convergence between traffic management system and electric vehicle.

With regard to pre-industry convergence, for each technology field we calculate the fraction of patents that were assigned by companies related to the technology field at hand or by companies related to the remaining three technology fields. In this case, we define the threshold value and the related range as 0.035–0.044 for weak or equal, and greater than 0.045 for strong pre-industry convergence. To return to the example of the traffic management system: If the fraction of traffic management system related patents assigned by a company from one of the remaining technology fields exceeds 0.045, we define this as a strong one-way pre-industry convergence. If the reverse relation is also observable, we define it as a strong two-way pre-industry convergence.

V. RESULTS

In this section, we present the results of our analysis. For this purpose, we proceed in two steps. First, we start with a general assessment, in which we examine and compare technology and pre-industry convergence. This step is not time related, i.e., we define a movement as converging, once the threshold value is exceeded, regardless of the timeframe in which it occurs. Second, we conduct a time-related assessment in order to reveal time lags between both convergence types. In particular, we focus on timeframe 2 and compare whether the convergences identified in the general assessment were already evident in timeframe 2. See Tables V and VI for the numeric values of our assessment in the course of time.

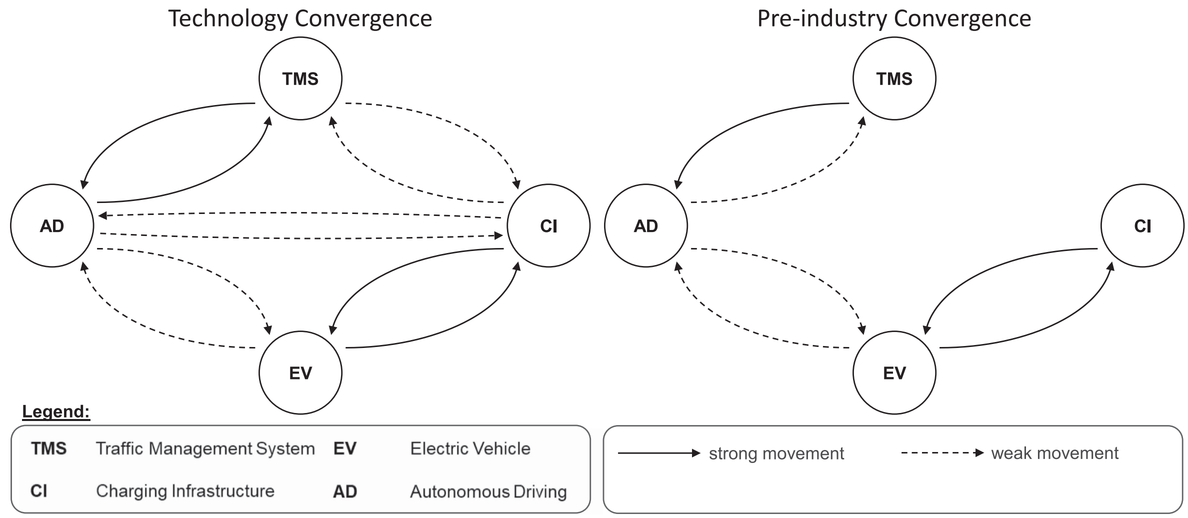

Fig. 4. Convergence map as result of general assessment. Based on the threshold value, a solid line shows a strong movement and a dotted line reflects a weak movement. Source: Authors.

A. General Assessment

A general assessment of convergence on the technology and pre-industry levels reveals numerous convergence movements. Some of these occur in parallel, some do not.

With regard to technology convergence, we identify five convergence movements, namely two cases of a strong two-way convergence and three cases of a weak two-way convergence (see Fig. 4). In particular, we observe a strong two-way technology convergence between autonomous driving and traffic management system, and between electric vehicle and charging infrastructure. In addition, we identify a weak two-way convergence between traffic management system and charging infrastructure, autonomous driving and charging infrastructure, and autonomous driving and electric vehicle.

With regard to pre-industry convergence, we observe three convergence cases. We identify one strong two-way convergence, one moderate two-way convergence, one weak one-way convergence. For instance, the strong two-way convergence takes place between electric vehicle and charging infrastructure, whereas a moderate two-way convergence occurs between autonomous driving and traffic management system. Furthermore, we observe a weak one-way convergence between autonomous driving and electric vehicle.

A comparison of convergences on both levels reveals that pre-industry convergence is often identical to technology convergence. Nevertheless, there are some differences, in which there is an indication of technology convergence, but no indication of pre-industry convergence. A major difference between both levels becomes evident in cases of infrastructure-related technologies, namely traffic management system and charging infrastructure. More specifically, in cases of pre-industry convergence (as opposed to technology convergence) we find that the convergence from autonomous driving to traffic management system is weaker and there is even no convergence between charging infrastructure and traffic management system, regardless of direction. Furthermore, in contrast to the weak two-way technology convergence, there is no pre-industry convergence between autonomous driving and charging infrastructure.

These deviations might be due to three reasons. First, infrastructure-related technologies seem to require a deep, specialized technical know-how, which makes it difficult for companies from distant industries to enter the market. By analyzing the CPC distribution of all four technologies by means of the Herfindahl–Hirschman Index[5] (HHI), this assumption can be confirmed, as it shows a high concentration for traffic management system and charging infrastructure (see Table VII). Second, high market barriers caused by patenting activities of incumbent companies might also deter distant companies from entering a market. This is true for the traffic management system, where incumbents started patenting early and achieved significant technical progress through their lead-time advantage. Third, we assume that small and specialized incumbent companies, which are recognizable by a relatively modest patent portfolio size (see Table VII), do not enter into distant technologies, even if their patents address distant technologies. This leads to a lack of pre-industry convergence, whereas technology convergence may occur. We consider this to be one possible explanation for the absence of pre-industry convergence from charging infrastructure toward either autonomous driving or traffic management system, since charging infrastructure incumbents are characterized by a small patent portfolio on average (see Table VII).

B. Time-Related Assessment

To assess time-related convergence, we expand Fig. 4 by considering the convergence movements in timeframe 2. In particular, we compare the convergence movements from our general assessment and examine whether any convergence movement

[5]The HHI is a concentration metric (for formula see [32]). In our analysis, the shares in the formula depict the proportion for a CPC class. Since we use integers rather than decimals, our results range between 0 and 10 000, where an HHI above 2500 represents high concentration.

TABLE VII
HHI AND AVERAGE PATENT PORTFOLIO SIZE FOR EACH TECHNOLOGY

Technology	HHI	Average patent portfolio size
Autonomous Driving	1457	65.30
Electric Vehicle	2084	30.35
Charging Infrastructure	4008	9.42
Traffic Management System	4592	77.25

Source: Authors

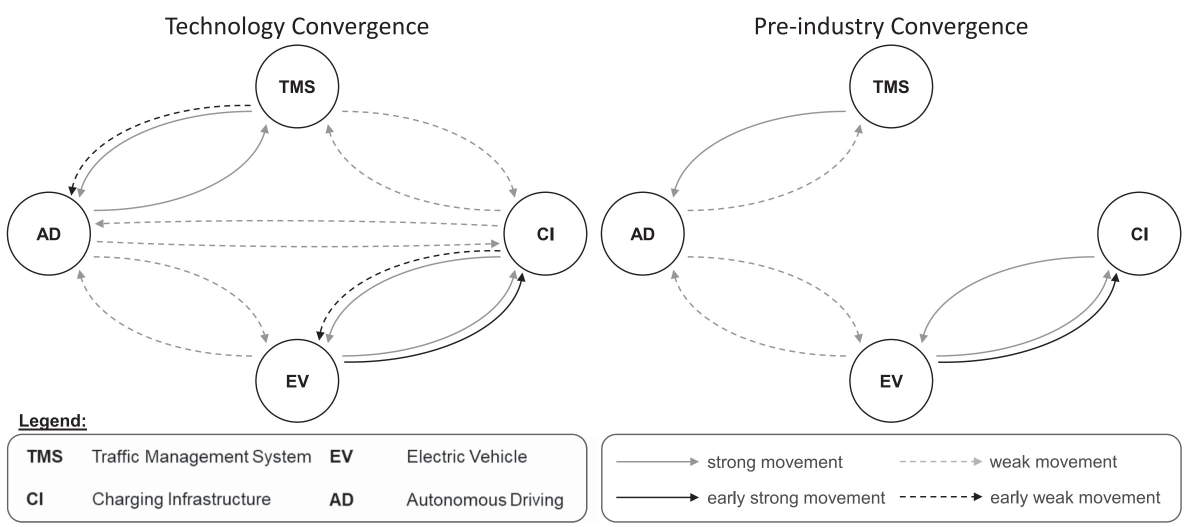

Fig. 5. Convergence map as result of time-related assessment. A gray line reflects a general assessment, whereas a black line indicates an early movement. Based on the threshold value, a solid line shows a strong movement and a dotted line reflects a weak movement. Source: Authors.

already became apparent in timeframe 2. We label respective cases as early signals of convergence (see Fig. 5).

In terms of technology convergence, we observe three early convergence movements. We see two early weak convergence movements: one from traffic management system to autonomous driving, and one from charging infrastructure to electric vehicle. In addition, we observe an early strong convergence from electric vehicle toward charging infrastructure.

With regard to pre-industry convergence, we only observe one early strong convergence from electric vehicle toward charging infrastructure.

A comparison of both convergence levels reveals four interesting facts. First, there is no case in which pre-industry occurs earlier than technology convergence. Second, many cases go hand in hand, especially where early signals are absent. Third, there is one case of early convergence—between electric vehicle and charging infrastructure—that occurs on both levels. Fourth, there are two interesting cases, in which technology convergence takes place earlier than pre-industry convergence.

In order to understand why technology convergence may occur earlier than pre-industry convergence, we take a closer look at the assignees of convergence-driving patents[6] in timeframe 2. Table VIII depicts the top six assignees of convergence-driving patents from charging infrastructure to electric vehicle and from traffic management system to autonomous driving. Analysis of the assignees shows that in both cases the respective companies have diverse backgrounds, e.g., automation or transport technology. Therefore, we assume that the early technology convergence was driven by application-oriented companies, which used these technologies within their particular niches rather than for the idea of smart mobility. Consider the example of *Precision Automation Systems, Inc.*, whose convergence-driving patent (US5545967) deals with an automatic battery management system for forklift trucks and automated guided vehicles in factory environments. Another example concerns the patent

[6]A patent is labeled as convergence-driving if its similarity value to a semantic anchor point ranges above the 90% quantile.

TABLE VIII
OVERVIEW OF TOP SIX ASSIGNEES OF CONVERGENCE-DRIVING PATENTS

Convergence-driving patents (CI to EV)		**Convergence-driving patents (TMS to AD)**	
Assignee	**# patents**	**Assignee**	**# patents**
Norvik Traction Inc.	3	Condition Monitoring Systems	1
Hughes Aircraft Company	2	Omron Corporation	1
Kabushiki Kaisha Toyoda Jidoshokki Seisakusho	2	Pulse-Com Corporation	1
Honda Giken Kogyo Kabushiki Kaisha	1	Rockwell International Corporation	1
Precision Automation Systems, Inc.	1	Schwartz Electro-Optics, Inc.	1
Hubbell Incorporated	1	Union Switch & Signal Inc.	1

While the left column depicts assignees of convergence-driving patents from charging infrastructure toward electric vehicle, the right column contains assignees of convergence-driving patents from traffic management system toward autonomous driving.

(US5214793) of *Pulse-Com Corporation,* which refers to a communication system for sending location-specific commercials to vehicles.

VI. CONCLUSION

In this article, we examined the interplay between technology and industry convergence. For this purpose, we operationalized the concept of pre-industry convergence in a novel way. Pre-industry convergence describes the idea of a very early stage of industry convergence in which not a group of companies but individual companies start patenting in distant industries as an expression of their convergence efforts and aims. We proposed a patent-based approach to jointly measure the convergence on the technology and pre-industry levels. By applying our method to the case of smart mobility, we identified several convergence movements and examined the relationship between both convergence levels. Our analysis reveals that technology and pre-industry convergence often occur simultaneously, but under specific conditions, e.g., with high market and technology barriers, there is either no connection at all or a time-lagged connection.

Our article bears several theoretical implications. By integrating the concept of pre-industry convergence, we expanded the sequential model of convergence. In addition to this, we established the idea of the market entrance of companies from distant industries as a proxy for pre-industry convergence, thus complementing the idea of collaborations as a source of pre-industry convergence [5]. Furthermore, our findings confirmed that technology convergence is a possible indicator of industry convergence, since technology and pre-industry convergence occur simultaneously several times. However, we identified four conditions under which there is either no connection at all or a time-lagged connection between both convergence levels. In particular, there is a lack of connection when entering a technology field requires deep and specialized technical know-how or when high market entry barriers exist, caused by incumbent companies that started patenting in a technology field at an early stage. Additionally, small and specialized incumbent companies do not drive pre-industry convergence, as they do not enter distant markets, even if they address these technologies in their patents. In general, it seems that for companies from distant industries entering infrastructure-related technologies is more difficult than entering product-related technologies. There is a time-lagged connection if pre-industry convergence follows technology convergence with a delay. This case occurs if technology convergence is initially driven by application-oriented companies, which exploit these technologies for their niche markets.

Our article also bears several managerial implications. The method can be used as an early-warning system for industry convergence. A tool like this can be valuable for incumbents as well as for distant companies. Incumbent companies may apply our approach to identify early signals of an upcoming industry convergence. This lead-time advantage can be used to prepare for the technical change by, for instance, a repositioning of R&D or seeking collaborations. In contrast, distant companies may use our method to monitor their competitors and identify new business opportunities. Furthermore, our approach may help distant companies identify promising technology fields in which convergence is not chiefly driven by incumbents.

Apart from these implications, this article still faces several limitations in terms of the data source, method, and treatment of companies and assignees. While the first two types of limitation concern technology convergence as well as pre-industry convergence, the third type only concerns pre-industry convergence. Three limitations are due to our datasets: Basically, we rely on patent data, which could be complemented by other sources. For instance, websites could be crawled to obtain additional information about companies' movements to distant technologies. Going more into detail, our data are characterized by a low recall measure. Although a high precision is necessary for our analysis, a low recall implies that our analysis is based on a reasonable subset of all relevant patents. Furthermore, our patent sets are distributed unequally across the timeframes. More specifically, the number of patents in recent timeframes is much higher than in earlier ones. This is the case because smart mobility is a young and growing field of technology. However, it entails consequences for our analysis, such as a bias in forming semantic anchor points. Two of the paper's limitations concern our method. Regarding its external validity, the method is limited to technological fields that have a high proximity to patenting. Another limitation relates to the threshold values, since different settings for these values may lead to different results. There also are two limitations related to the analysis of pre-industry convergence: We assign a company to one technology field only, based on its most frequent primary CPC. Consequently, we neglect that companies may be active in several technology fields at once. Furthermore, although we standardize assignee names, some assignee names may still remain unstandardized. So, even though we carry out several random sample tests, there is still a possibility that individual companies appear twice due to differences in spelling.

We would like to suggest some starting points for further research. Most promisingly, the question regarding the interplay between technology and pre-industry convergence could be deepened in several ways. For instance, one might focus on nonrelated or time-lagged cases and perform a qualitative in-depth analysis of causes. For this purpose, more cases from other industries should be identified and examined, in order to provide technology-independent and generalized answers. In addition, it might be interesting to analyze whether the early patentees of convergence also are the winners later. This question can be coupled with a qualitative approach to identify the possible determinants that may favor or hinder the success of early patentees. Furthermore, our research question can be extended to other combinations of convergence levels, such as science and market or science and industry. Moreover, alternative data sources can be combined with our approach. For instance, patent families could be used instead of single patent documents. Also, the approach of [5] can be coupled with our patent-based approach for an enriched and more comprehensive analysis. In contrast, a comparative study comparable to [5] can be carried out to validate our results and to reveal the advantages and disadvantages of both methods with regard to industry convergence. Finally, there is also potential for methodical improvements. A machine learning based algorithm, such as topic modeling, can be applied to measure similarities [33]. Furthermore, assuming that a large amount of data is available, the use of deep-learning models is conceivable. Deployment thereof can range from simple tasks like entity recognition (recognize assignee names and industries) to complex forecasting approaches [8], [34].

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