# Editorial
# Deciphering Convergence: Novel Insights and Future Ideas on Science, Technology, and Industry Convergence

## I. Introduction and Motivation

CONVERGENCE can be thought of as a "megatrend" that brings different industries, technologies, and scientific disciplines together [1]. Moreover, today's grand challenges will not be solved by one discipline, one technology, or sector alone. The U.S. National Science Foundation recently set up a research funding program dedicated to "convergence research." The aim is to integrate different research fields, actors, and sectors to foster the rise of novel technology systems based on convergence. For example, the synthetic biology research center emerges at the interface of engineering, data science, and biology. Convergence refers to the growing together of different industries that were previously largely separate from each other. For example, the convergence of the telecommunications and computer industries, initiated by the digitization of data, has led to hybrid products such as smart phone.

Despite its empirical relevancy, the concept of convergence is still fuzzy [1]. The etymology of the verb converge has its roots in the Late Latin (c.a. 1690s) meaning "to incline together" (from com– "together" + vergere "to bend"). It describes either multiple discernable items moving toward union or the merging of distinct technologies, devices, or industries into a unified whole [2]. Convergence is already taking place in a number of industries, such as biopharma, nutrition products, health care, energy, media and communications, smart cities, and telecommunications equipment industry [3], [4], [5], [6], [7], [8], also enabled by the digital transformation [9].

The integration of formerly distinct scientific disciplines, related technological fields, regulatory frameworks, or entire industries directly affects researchers at universities and research institutions as well as firms, particularly in research-intensive high-tech sectors [1], [10], [11], [12]. Firms may face severe competency gaps and path dependencies become evident because competences are industry specific and evolve slowly [13], [14]. The usage of (new) knowledge as well as the collaboration with or even the acquisition of technological gatekeepers to overcome competency gaps and path dependency therefore becomes highly relevant [3], [15]. To conclude the phenomenon of convergence is opening up new business and growth opportunities but it also comes along with a number of challenges as it: changes the way in which customers perceive new products and technology functionalities [16]; forces companies adapt their innovation strategies to build novel competences [15]; and accordingly, to rethink their business models [17] and supply chain strategies [18], [19]; and paves the way to leverage upon intangible characteristics, like new meanings [20], reshaping the concept of radicalness in specific industries. In addition, the speed to which convergence occurs may have strategic influence on how specific technological sectors redesign the competitive landscape. Thus, the blurring of the boundaries between industries has become a pervasive and growing phenomenon [21], that research is not paying sufficient attention on.

Notwithstanding its relevance, academic literature providing insights into convergence is rather scarce and not able to advice firms on how to manage the challenges it generates (e.g., [1], [2], [21], and [22]). It is important to note that while previous research has been valuable in filling some knowledge gaps around convergence, it has failed to provide sufficient evidence of the strategic interplay between the four types of convergence. Therefore, further exploration and investigation into this topic is crucial in deepening our understanding of convergence. Time has come to push forward the horizon of possible methods, techniques, and frameworks assessing the strategies to reach convergence from the four perspectives mentioned earlier.

## II. Literature Review

In line with extant studies, we adopt a sequential view on the convergence process starting with converging scientific or knowledge fields to technologies and markets or applications finally leading to industry convergence [2], [23].

The first step deals with *scientific convergence*, which entails distinct scientific disciplines that are beginning to cite each other and collaborate [2]. Hence, the convergence process starts with a decreasing distance between formerly distinct scientific or knowledge fields manifesting in cross-disciplinary scientific research. Coccia and Wang [24] argue that, over long time periods, institutional research collaboration plays an important role in shaping the scientific landscape and its intersections, and that the latter can pave the way to breakthroughs. Coccia and Bozeman [25] expand upon that by building an allometric model through which they unveil patterns of collaboration within and between disciplines. An additional contribution to the debate on scientific convergence is also provided by the many studies

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investigating interdisciplinarity in science through bibliometrics (see, e.g., [26], [27], and [28]).

The next step is *technology convergence*, characterized by an increasing overlap of formerly independent und unrelated technological fields. Technology convergence occurs when the distance between applied science and technology development decreases [2], [29], [30]. To provide some examples of the studies carried out in this domain, Han and Sohn [31] focus on the determinants of the convergence in standards related to information and communication technologies (ICTs); Jeong and Lee [22] provide an overview of the drivers of technological convergence using data from government-supported R&D projects in South Korea; Karvonen and Kässi [32] generate novel patent analysis methods to find ways for anticipating the early stages of technological convergence; and Borés et al. [33] focus on the economic and strategic motivations inspiring firms to catch up the technological convergence in the ICT sector.

The following step describes the *convergence of hitherto separate markets* or fields of application, leading to new product-market combinations, which materializes in the form of convergent products [1], [34]. Schmidt et al. [35] find a link between the exploitation of customer-specific synergies and the endogenous market convergence, while Griffith [36] develops a multilevel institutional approach to shed light on market segments convergence effects. In addition, Gill and Lei [37] assess market convergence in the electronics sector by looking at the role of new functionalities added to products.

*Industry convergence* as the emergence of a new subsegment completes the process of convergence, also reflected by a converging governance structure, e.g., standards and regulations for convergent products [38]. In addition, convergence can be distinguished by its origin, i.e., supply (science and technology driven) and demand-side (market driven) convergence [5], [39], [40].

Hence, industrial convergence is the fusion of firms or industry segments [2], [21], [39], resulting from a complex series of events unfolding over time and starting with convergence occurring in science, technology, and then market. Such a complexity, for instance, can entail either knowledge recombination dynamics in closely related fields [41], [42], or searching mechanisms [72], [73] whereby agents try to scout new intersections and generate new fields of investigation, establishing strategic collaborations with partners having distant technological expertise [43], or deploying acquisition strategies through alliances [6]. Specifically, Geum et al. [44] provide empirical evidence of successful Korean cases of industrial convergence by outlining a first taxonomy; Preschitschek et al. [45] assess the convergence of industries by measuring the semantic similarity of the patents within specific technological fields finding inconsistencies in using only IPC coclassification analyses; Christensen [46] looks at the trajectories of complementary convergence claiming the importance of mergers and acquisitions as a central means for realizing convergence; and Katz [47] discusses about the formation of new industry segment out of convergence in telecommunications and computer industries.

A recent review of the convergence literature rooted in technology and innovation management research [1] identified four different strands of research as illustrated in Fig. 1. These span from (1) drivers and patterns of convergence, (2) anticipation of convergence, (3) strategic reaction to convergence, and (4) convergent products, which all emerge in response to different challenges of convergence.

The work related to the strand (1)—drivers and patterns of convergence—explores the mechanisms that trigger and drive convergence processes as well as the patterns in which convergence evolves over time, including different types of convergence. Convergence processes can be initiated by new technological developments [42], [48], changes in demand [35], or evolving regulation and standards [31]. Patterns of convergence, e.g., comprise the distinction between substitutive and complementary convergence [49], [50] or inter- and intra-industry convergence [51].

The strand (2)—anticipation of convergence—builds on the steps of the convergence process (science, technology, market, and industry convergence) to forecast convergence movements at an early point in time. Heavily relying on informetrics, research in this strand focuses on new method development, mostly based on patent data, as well as detecting emerging areas of convergence [51], [52], [53].

The largest portion of convergence research relates to the strand (3)—strategic reactions to convergence—and revolves around forming company strategies to respond to the challenges arising in converging environments. Based on the resource-based view (RBV), the contributions examine internal factors that enable firms to develop strategic reactions such as the technological knowledge base of a firm [54], knowledge integration [55], business models [56], or product portfolios [12]. External factors, drawing on the relational view of the firm, include collaborations, networks, and open innovation [10], [15], [57], [58].

In contrast, the strand (4)—convergent products—has attracted the smallest group of studies. Convergent products, also known as converging, hybrid or borderline products, combine functionalities from formerly different product categories [59]. Studies explore success factors for convergent products, mainly taking a consumer and product view [60], but also from a firm perspective [61].

In summary, convergence research as an emerging area has often been inward-focused, to first understand the phenomenon of convergence, how it comes about and how it unfolds. This has lead to a disconnect at times between the scientific discussion within the field of convergence and its theoretical foundations in technology and innovation management and neighboring disciplines [1]. Hence, the major challenge for convergence research is a firmer anchoring in the theoretical underpinnings outlined in Fig. 1. The framework connects current challenges in convergence research for each strand with emerging topics and potential theory lenses to tackle these challenges, thereby serving as a reference point for the contributions in this special section.

## III. Summary and Positioning of the Contributions in the Convergence Research Landscape

The articles in this special section contribute to our understanding of convergence from a variety of perspectives.

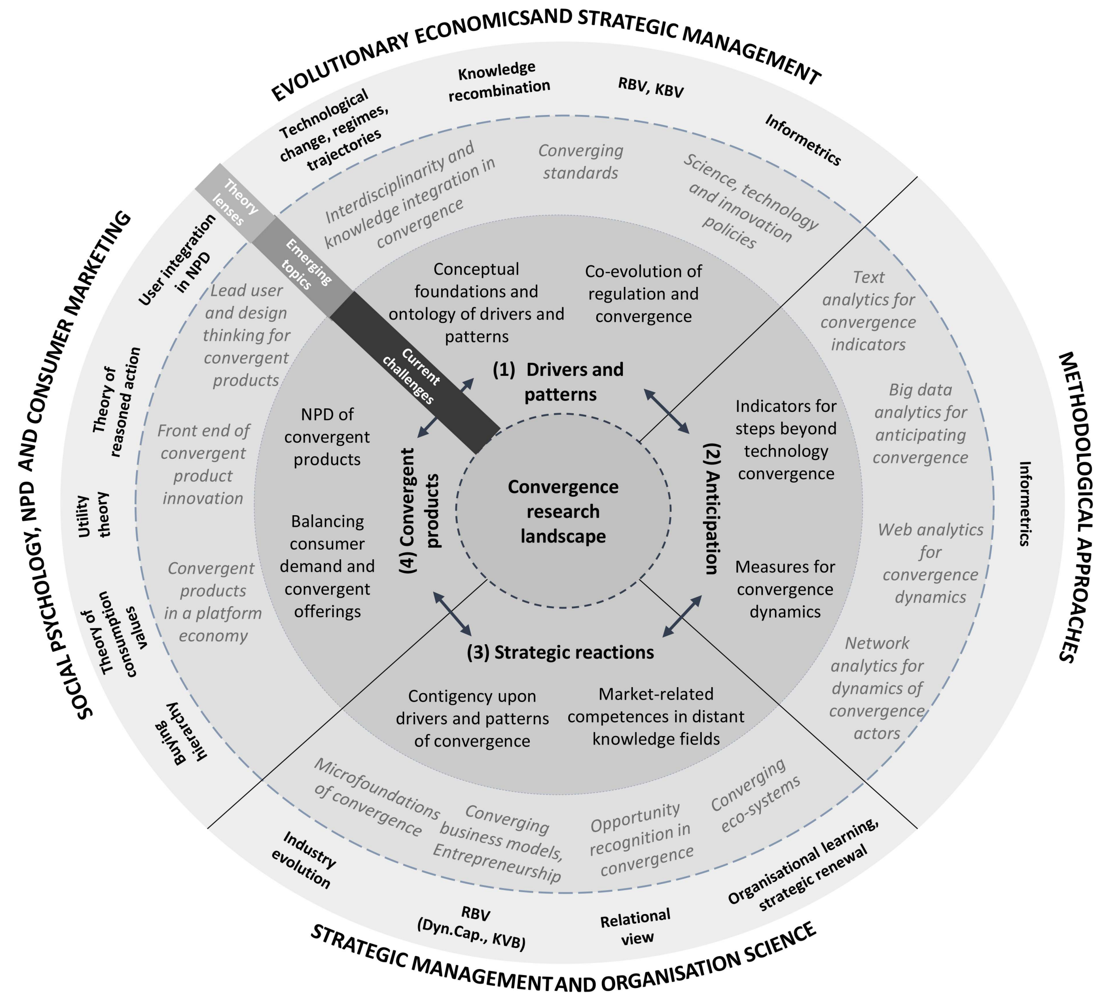


Fig. 1. Framework of convergence research, integrating theoretical perspectives on convergence research and main challenges, matched with emerging topics [1].

In light of the aforementioned framework for convergence research Nguyen and Moehrle [62] contribute to the research strand (1) "drivers and patterns of convergence" by exploring the concept of technology convergence in the context of urban innovation and sustainable development. The authors study technology convergence in the United States from 1976 to 2014 using a measure of CPC patent coclassification analysis. They propose a new conceptual approach for analyzing technology convergence, which includes vertical, horizontal, and interplay analyses. The authors discover strong fusion among four different systems (vertical convergence), within the super-system (horizontal convergence), and between system levels and elements of the super-system (interplay) in urban innovation through their analysis. The authors also make three broad conclusions. The first is that technological movements occurred in parallel. They found that three system levels, namely the core system, subsystem, and associated system moved toward the super-system. Many movements occurred in parallel between the elements of the super-system. The second finding is that some technological movements were related. In urban innovation, electricity and communication seem to be the "spider in the web." Not only did many other elements of the super-system move toward electricity and communication, but the associated system moved at least moderately as well. The third finding is that some technological movements were unrelated. There seems to be a separate development of the core system and subsystem. They move only weakly toward electricity and communication. In contrast, the core system moves slightly toward water and hydraulic engineering. The authors suggest differentiating between three types of constellations in the relationship between horizontal and vertical convergence analysis. The first type is when there is no interplay between technologies on different system levels. In this case, researchers can do the horizontal convergence analysis without considering any bias from outside. The second type happens if researchers can identify driving technologies. Driving technologies come from outside the horizontal level; they move toward elements on the horizontal level, which move toward other elements on the horizontal level. Researchers have to consider these driving technologies in order to fully understand convergence on the horizontal level. The third type lies between the first and second types. Researchers can identify technologies from outside the horizontal level; they move toward elements on the horizontal level, which do not move toward other elements on the horizontal level. Researchers have to be careful with these technologies, but they can still do the horizontal convergence analysis without having an important bias. In conclusion, the authors suggest that the research may stimulate analysts in companies and other organizations in several ways, both from a methodical as well as from a content-oriented view. From a methodical view, analysts can learn from this study to be aware that convergence on a horizontal level may be driven by inside as well as outside factors, belonging to other system levels. They can use this article as a framework for their own analysis and consider the different types of constellations in the relationship between horizontal and vertical convergence analysis in order to fully understand the process of technology convergence.

Yang et al. [63] also contribute to the research strand (1) "drivers and patterns of convergence" by taking a regional perspective and render novel measures to assess this perspective. They examine the factors that contribute to regional innovation convergence in China, using data from 30 provinces from 2005 to 2016. The authors use two measures, $\sigma$-convergence and $\beta$-convergence, to analyze the data and consider the effects of spatial factors and high-tech industrial agglomeration on regional innovation convergence. The study finds that there is a significant spatial autocorrelation in China's regional innovation, which suggests that previous studies that used ordinary least squares methods may have obtained biased estimates of regional innovation convergence. This highlights the importance of considering spatial effects when analyzing regional innovation convergence. The $\sigma$-convergence analysis shows that there is $\sigma$-convergence in China's regional innovation over the sample period, meaning that the gap in regional innovation between provinces is gradually narrowing. The study also finds that China's regional innovation has both absolute and conditional $\beta$-convergence, which means that provinces with lower levels of innovation tend to have a faster rate of growth in innovation compared with those with higher levels. The study also finds that high-tech industrial agglomeration can promote regional innovation convergence. This is because high-tech industries generate knowledge spillovers that can benefit other industries and regions. The study also finds that factors, such as physical capital investment, R&D expenditures, human capital, and trade openness can help increase regional innovation. The study also looks at the effects of subhigh-tech industrial agglomeration on regional innovation convergence and finds that industrial agglomeration in certain subindustries, such as electronic and communication equipment, computer and office equipment, and instruments and meters, can speed up regional innovation convergence. However, industrial agglomeration in other subindustries, such as pharmaceutical and medical equipment and aircraft and spacecraft, does not have the same positive effect. Overall, the study suggests that policy measures should be taken to promote economic cooperation and knowledge sharing between provinces, as well as targeted policies and regulations to support regional innovation in provinces with lower levels of innovation. Additionally, more support should be provided for the subindustries that are found to be more conducive to regional innovation convergence.

The study of Hong and Lee [64] presents another contribution to the growing research body focusing on the "drivers and patterns of convergence" processes. The authors perform a comparative analysis to investigate the most effective classification algorithms and indexes of structural proximity for predicting technology convergence. The study uses the Wikipedia database as a source of data, as the relationships between technologies defined using Wikipedia hyperlink information is considered to be more precise and concise than using patent citation or co-classification. The study follows several steps in its comparative analysis. First, Wikipedia hyperlink networks are constructed to represent the relationships between technologies of interest for different time periods. Second, 10 indexes of structural proximity that measure three different aspects of relationships between technologies (i.e., technological similarity, technological distinctiveness, technological universality) are computed for unconnected pairs of nodes from each of the Wikipedia hyperlink networks. Third, a set of classification models are developed that categorize unconnected pairs of nodes in each network into two groups according to their expected link status in the target period of interest. The study found that the random forest algorithm should be given preference to produce a well-performing link prediction approach to anticipating converging technologies in the next one, three, and five years. The random forest algorithm generates the classification models with high performance across different indexes, and it produces better performance when combined with indexes that measure technological distinctiveness. At the forecast horizon of 10 years, the support vector machine (SVM) outperformed other algorithms. The study suggests that the emergence of technology convergence is predictable to some extent through the supervised link prediction approach, and that random forest and SVM are effective in anticipating technology convergence in the short-term and mid-term future, respectively. With respect to the structural proximity indexes, the study found that the indexes measuring technological distinctiveness (i.e., RA and AA index) were particularly effective for anticipating technology convergence. The study also found that the performance of the models improved as the forecast horizon increased.

Ardito et al. [65] add to our understanding of how to anticipate convergence processes, thus, contribute to research strand 2 "anticipation of convergence." The article discusses the concept of technological convergence and its increasing relevance in creating new markets and disrupting existing ones. Technological convergence refers to the merging of different technologies, industries, and disciplines into one, creating new products, services, and markets. Emerging trends, such as the increasing complexity of new products, their miniaturization, digitalization, and architectural changes, have been highlighting that new technologies are often the result of technological convergence processes. Therefore, understanding the antecedents of the technological convergence process is paramount to support firms in establishing or sustaining their competitive advantage. The authors of the article take a search and recombination perspective to understand how the technological search breadth and geographical search breadth of a focal technology influence the likelihood and speed of technological convergence events. They define technological search breadth as the extent of different knowledge components belonging to different technological domains that can be recombined to create new solutions. Geographical search breadth, on the other hand, is defined as the extent of different pieces of knowledge originating in diverse geographical domains that can be recombined. Through empirical analysis, the authors found that the extent of technological search breadth positively affects both the likelihood and speed of the technological convergence process. This is because expanding the knowledge components belonging to different technological domains that can be recombined increases the variety of technological solutions to be scrutinized, leading to the development of valuable and original solutions that favor technological convergence. Moreover, the higher technological search breadth supports the development of creative and radical solutions that may be promptly applied to solve technological issues in different domains, eventually increasing the speed of technological convergence. On the other hand, the authors found that the higher the extent of different pieces of knowledge originating in diverse geographical domains, the lower the likelihood of convergence. This is because knowledge components from specific geographical areas may be characterized by local and context-specific approaches and routines, making it more difficult to search and recombine this knowledge, causing a decrease in the effectiveness of the process. Additionally, the costs of the knowledge assimilation may reveal themselves as higher than the benefits of the novelty, resulting in a decrease in the likelihood of a technological convergence event. Consistently with their hypothesis, the authors also found that the higher the extent of geographical search breadth, the lower the speed of a technological convergence event. The rationale of this is related to the need to assimilate the knowledge components originating in different geographical domains, which may increase the time required to achieve convergence. In fact, as the number of knowledge components from distinct geographical areas increases, the searching agent may need to increase the efforts, also in terms of time, to assimilate and integrate them. Eventually, this slows down the search and recombination process, in turn increasing the time to achieve convergence. In addition, the authors also analyzed the effects of the interaction between technological and geographical search breadths on their dependent variables. Consistently with their hypothesis, they found that the interaction between technological and geographical search breadths positively affects the likelihood of technological convergence. In particular, this result can be understood considering that having high technological and geographical search breadths means that the searching agent can recombine a higher number of knowledge components with different characteristics, thus expanding the recombinant space and increasing the likelihood of technological convergence.

Schiavone et al. [66] focus on the concept of industrial convergence and its implications during times of crisis, specifically the COVID-19 pandemic. Thereby, this study adds to our current understanding of convergence by exploring the context of crisis as a particular driver for industrial convergence (compare strand 1 as depicted in Fig. 1). More particular, industrial convergence refers to the merging of different industries, technologies, and disciplines into one, creating new products, services, and markets. The authors aim to explore possible business dynamics caused by convergence, such as the creation of new industries (e.g., the Med-Tech industry) or the emergence of hybrid figures to support data integration and aggregation in managing data and information in complex systems. To do this, the authors investigate the case of PM (precision medicine), which is becoming increasingly important for the verification of a range of therapies and vaccines in production within the healthcare context. With reference to the COVID-19 pandemic, the authors argue that through PM it is possible to identify and examine both a patient's carriers and positives who show symptoms and obviously confirm patients who have very advanced symptoms. Therefore, the new Med-Tech industry that is being created is particularly suitable for the treatment of the COVID-19 crisis. They also point out that the explorative case of PM shows a recourse to technological tools within the new Med-Tech industry during the COVID-19 pandemic in order to speed up healthcare processes and better manage patients' data and information. The authors also present three research propositions: P1: Industrial crisis increases the recourse to digitalization, P2: Industrial crisis leads to the creation of hybrid figures and processes, and P3: Industrial crisis increases the recourse to patient-centered business models. They argue that industrial crisis such as COVID-19 increases the need for digitalization in order to speed up healthcare processes and better manage patients' data and information. They also point out that industrial crisis leads to the creation of hybrid figures and processes, such as PM which is becoming increasingly important for the verification of a range of therapies and vaccines in production within the healthcare context. They also argue that industrial crisis increases the recourse to patient-centered business models, as the provision and management of data by users are important in the phase of industrial convergence, especially for the codevelopment of medical devices and the emergence of radical innovations as outcomes of convergence. In conclusion, the authors argue that industrial convergence is an increasingly widespread phenomenon today, and many new sectors have emerged from the integration and merger of sectors that previously existed separately. They also point out that in times of crisis, such as the COVID-19 pandemic, it is important to provide immediate and effective responses to eliminate the effects of the crisis. They also state that their findings offer theoretical implications to the growing stream of literature about industrial convergence, by better detailing the business dynamics during an industrial crisis such as the COVID-19 pandemic. They also note that cross-border companies find themselves operating in different markets in terms of geographical location and technical skills, and that a value-based perspective is at the same time outcome-based healthcare. They also point out that a PM application must be justified by a very strong diagnosis that accompanies that type of specific therapy, and that the creation of new business models, on the one hand, and the adoption of exponential technologies, on the other hand, have at their base the essential element of in-depth R&D activity that is able to make technologies not only effective but scalable for use and for the impact on health protection (prevention and then treatment), but also able to eradicate obsolete models.

Kim et al. [67] apply a network perspective to elucidate patterns of industry convergence, which present another contribution to the growing research strand (1) "drivers and patterns for convergence." More particularly, the authors discuss a sensitivity analysis conducted to examine the validity of a network analysis that looked at the relationships between different industries over three time periods (2010–2012, 2013–2015, and 2016–2019). The authors found that the results of the analysis were largely consistent across different time periods and that the method of dividing the periods did not significantly affect the results. To compare the results, the authors chose a five-year period and found that the derived clusters were almost the same: Internet and mobile, manufacturing and electronics, software and IT, commerce and tourism, financial services, and healthcare. The relationship between clusters (convergence rate) also appeared similar for the sensitivity analysis, indicating that the method of dividing the periods did not critically affect the result, supporting the validity of their approach. This article then goes on to discuss the implications of the analysis for startup companies. The authors found that startup companies in the early and mid-2010s mainly focused on mobile-focused convergence and related revenue streams. This was due to the rapid growth of mobile phone and connectivity, which led to the development of many app-based services that provided useful information based on users' behavior and location. According to the Crunchbase database, the number of startups founded in 2010 was 3494 and increased over time until mid-2010s, exceeding 10 000 in 2014. However, this number decreased over time and continued to drop to 9994 in 2017, 8691 in 2019, and 5982 in 2019. The big growth of startups is related to the emergence of new innovative services based on the growth of the mobile and IT industries. In fact, startup companies continued to increase in the early and mid-2010s and they achieved great growth through fast innovation and had a successful exit. Our results show that most companies have been acquired by companies in industries within similar industries. Companies included in Internet/mobile and manufacturing/logistics clusters tended to converge with similar industries. However, companies in financial and healthcare industries seem to converge with heterogeneous industries, implying business extension toward diversified applications. In particular, in the middle of 2010, which is period 2, convergence between different industries was more active than convergence within the industry. This indicates that many companies have attempted to expand their industries through convergence in this period. In addition, the rise of convergence with education industry was observed from 2017 to current, and this situation is especially true in 2020 when the COVID-19 outbreak affects the business environment. The growth of the education industry is not limited to period 3 and continues to increase in 2020 as well. However, this may be due to a special situation in which e-learning and education platforms have gained great popularity in the COVID-19 context, which will require monitoring afterward. Environmental and eco-friendly issues also appear to increase in 2020 and are likely to be related to the COVID-19 outbreak. Overall, this article suggests that the results of the network analysis were consistent across different time periods and that the method of dividing the periods did not significantly affect the results. The authors also found that startup companies in the early and mid-2010s mainly focused on mobile-focused convergence and related revenue streams and that most companies have been acquired by companies in similar industries. However, companies in the financial and healthcare industries tended to converge with heterogeneous industries, implying business extension toward diversified applications. The authors also observed a rise in convergence with the education industry from 2017 to the present, especially in 2020 due to the COVID-19 outbreak.

Giordano et al. [68] present a novel methodological approach that contributes to strand 2 "anticipation of convergence" by drawing on text-mining techniques to identify technologies from C4ISTAR (Command, Control, Communications, Computers, Intelligence, Surveillance, Target Acquisition, and Reconnaissance) documents. The study applied two Named Entity Recognition (NER) approaches: a rule-based approach and a gazetteer-based approach. It shows that the rule-based approach identified more technologies (883 out of 1090) but was less precise (26.68%) than the gazetteer-based approach (57.56%). However, the authors note that the precision does not impact the quality of the output, only the time needed for manual review. The article also discusses the results of a technological convergence analysis. It shows the distribution of technologies and their clusters over the years as well as the measures of knowledge evolution, such as birth, death, stability, merging, splitting, using a combined text-dynamic network methodology. The authors find that there is an impressive growth in the number of distinct technologies employed in the defense sector and a remarkable growth in the number of clusters of technologies. The authors also note that the Merging index is systematically larger than the Splitting index, confirming the process of technological convergence. They also point out that Merging is prevalent, suggesting a dynamic in which independent technologies are used together for the resolution of complex challenges and then create new clusters. The authors also find that the C4ISTAR field started to incorporate electronics in the 1960s and other computer-intensive technologies afterward. This is evident from the jump in the number of distinct technologies and clusters in the 1960s and the almost monotonically increasing trend thereafter. The authors also find that the Merging and Splitting indexes have grown in parallel, which suggests that these technological trends are complementary in generating the dynamics of recombination. The authors also suggest that the growth in the number of distinct technologies and clusters is accompanied by a turbulent dynamic, made visible by splitting and merging. This turbulent dynamic is remarkable since the field of C4ISTAR technologies has extremely long development project timelines and relatively slow adoption of radically new technologies. The authors also point out that Merging is prevalent, suggesting a dynamic in which independent technologies are used together for the resolution of complex challenges and then create new clusters, co-occurring on a regular basis on documents. This is consistent with the notion of systemic innovation suggested by some authors. Overall, the contribution suggests that the use of text-mining techniques allows for the identification of a large number of technologies from C4ISTAR documents. The study also shows that there is an impressive growth in the number of distinct technologies employed in the defense sector and a remarkable growth in the number of clusters of technologies. The authors also find that technological convergence is prevalent and that independent technologies are used together for the resolution of complex challenges, leading to the creation of new clusters.

Caferoglu et al. [69] expand the sequential view on convergence by adding the concept of preindustry convergence which enables managers to anticipate industry convergence. As such, this study contributes both to strand 1 "drivers and patterns of convergence" and strand 2 "anticipation of convergence." The authors begin by identifying five cases of technology convergence, including two examples of strong two-way convergence (between autonomous driving and traffic management systems, and between electric vehicles and charging infrastructure) and three examples of weak two-way convergence (between traffic management systems and charging infrastructure, autonomous driving and charging infrastructure, and autonomous driving and electric vehicles). The author notes that these cases of technology convergence are important because they can lead to new products and services, as well as increased efficiency and cost savings. In terms of preindustry convergence, the author identifies three cases, including one strong two-way convergence (between electric vehicles and charging infrastructure), one moderate two-way convergence (between autonomous driving and traffic management systems), and one weak one-way convergence (between autonomous driving and electric vehicles). The author points out that preindustry convergence is important because it can lead to new business models and increased competition. The author notes that there is often overlap between technology and preindustry convergence, but there are some differences, particularly in cases of infrastructure-related technologies. For example, the author observes a weak two-way technology convergence between traffic management systems and charging infrastructure, but there is no indication of preindustry convergence in this case. The author also notes that there is no preindustry convergence between autonomous driving and charging infrastructure, despite the weak two-way technology convergence in this area. The author suggests that these differences may be due to factors such as the specialized technical knowledge required for certain technologies, high market barriers caused by patenting activities, and small and specialized incumbent companies not entering distant markets. The author also uses the Herfindahl-Hirschman Index to show that there is a high concentration of patents in traffic management systems and charging infrastructure, which may make it more difficult for companies from other industries to enter these markets. This article also examines time-related convergence, noting that some convergence movements that were not apparent in the general assessment became more pronounced over time. The author identifies three cases of early convergence in terms of technology convergence, including autonomous driving and traffic management systems, autonomous driving and electric vehicles, and electric vehicles and charging infrastructure. The author suggests that these early signals of convergence indicate that these areas will continue to evolve and converge in the future. Overall, they provide a detailed analysis of the concept of convergence in the context of technology and preindustry, highlighting the different types of convergence that can occur, as well as the factors that can influence the convergence process. This article also notes the importance of examining time-related convergence to better understand how convergence movements are evolving over time.

By employing a microfoundations perspective Hacklin et al. [70] contribute to both: the body of literature on "anticipation of convergence" (strand 2) as they render novel measures enabling the assessment of scientific convergence – second, their study also highlights the team composition which relates to the comparably small body of research on "strategic reactions to convergence" (strand 3). By drawing on a bibliometric dataset Hacklin et al explore the microfoundations of early-stage convergence in the information and communication technology (ICT) industry. The literature review found that prior research and theory have not devoted significant attention to the individual-level mechanisms underlying convergence, especially in terms of scientific convergence as a precursor to technological and industry convergence. The authors develop two measures for scientific convergence: knowledge reuse and boundary spanning, which both indicate that convergence can be observed as early as the 1960s—decades before industry convergence. The authors found that, at first, knowledge reuse (scientists drawing on similar papers across fields) shapes the convergence process, but boundary spanning (scientists authoring in both fields) shapes it more prominently in later stages. This suggests that early-stage ICT convergence happened in two consecutive waves, and is associated with two different micro-level behaviors—first by scientists "looking," and second by "walking," across different fields. The authors also found that larger author teams struggle to contribute to convergence, and larger teams have less of an impact on knowledge reuse and boundary spanning. The authors note that this is an important finding, as larger teams are often seen as more effective and efficient in creating new knowledge. The authors contribute to prior research examining convergence in three ways. First, they provide a more nuanced understanding of how micro-level convergence mechanisms develop and change over time. Second, they highlight how knowledge reuse and boundary spanning are two distinct micro-level behaviors underpinning convergence, which can help researchers develop more effective frameworks for explaining and assessing convergence. Third, they suggest that these two measures (knowledge reuse and boundary spanning) are suitable indicators to include when attempting to anticipate industry convergence, and can be used as early indicators of technology convergence. Overall, the article provides a detailed analysis of the microfoundations of early-stage convergence in the ICT industry, highlighting the different types of convergence that can occur, as well as the factors that can influence the convergence process. The article also provides insights into how larger teams may struggle to contribute to convergence, and the importance of knowledge reuse and boundary spanning as indicators of early-stage convergence.

In reflecting the entire research body of convergence by means of a literature review Klarin et al. [71] shed further light on the different research perspectives and identify clusters of convergence research. More specifically, the authors use a dataset of

857 publications to create a taxonomy of convergence scholarship. The study aims to identify the disparate research streams on convergence and create a mapping of the data to identify major clusters of convergence scholarship. The study finds the following six major clusters of convergence scholarship:

1) Industry convergence.
2) Media and communication convergence.
3) Market, club, and cluster convergence.
4) Impact of convergence on learning and development.
5) Industrial convergence.
6) Regulatory oversight and user adoption.

The red cluster, industry convergence, discusses convergence from the perspective of the "blurring of boundaries between two or more industries" The research within this cluster adopts the current dominant stepwise perspective of industry convergence and highly occurrent terms related to established industry convergence methodologies are reflected in this cluster. The green cluster, media and communication convergence, has the overarching theme of communication technology convergence, covering topics related to media convergence and the communication industry developments. The blue cluster, market, club, and cluster convergence, illustrates the aspects of political, economic, technological, and social differences among markets or countries and how such differences will decrease as industries move toward the "uniformity" of "pluralistic industrialism." The yellow cluster, impact of convergence on learning and development, illustrates the study of how convergence is affecting the learning and development process. The lilac cluster, industrial convergence, examines convergence from the perspective of how it is affecting the development of industries and the aqua cluster, regulatory oversight, and user adoption, illustrates the study of how convergence is affecting the regulatory oversight and user adoption process. This article provides a detailed analysis of each cluster, discussing the key themes and references within each one. It also presents a typology of convergence concepts, highlighting the distinction between industry convergence, industrial convergence, technology convergence, and technological convergence. Industry convergence refers to the blurring of boundaries between industries, while industrial convergence refers to the convergence of industrialization in a country or region. Technology convergence is about new technological combinations in products and/or services, while technological convergence refers to a process by which different industries come to share similar technological bases. This article also suggests that the traditional model of convergence, proposed by other studies, may not always be the case. The traditional model of convergence is a linear process where scientific convergence leads to technology convergence, which leads to market convergence and ultimately industry convergence. The authors of this article propose an alternative process called market-driven convergence, where companies first identify customer needs and technological trends, followed by research and development and resulting in Industry convergence in the long term. This process is particularly evident in the service industries where the rise of digitization redefines convergence and the process begins with no specific laboratory-dependent scientific breakthroughs. The contribution also notes that some convergence processes cannot be explained by the currently adopted processes proposed by other studies. For example, when the authors examine the green cluster related to media convergence, they found that media giants like CBS carried out market research first instead of conducting scientific developments in research centers as the first step. This highlights that in certain industries like service industries or others that do not necessarily depend on technological advancements, the process of convergence may start with market orientation, followed by technology convergence, market convergence, and ultimately industry convergence.

## IV. Future Research Avenues

This special section includes contributions to our current understanding of convergence that are both inspiring and useful for future research. Interestingly, the focus of the studies in this special section seems to center around strand 1 "drivers and patterns of convergence" as well as strand 2 "anticipation of convergence." The tendency to contribute to the drivers and patterns has also been observed in the literature review by Sick and Bröring [1] and seems to reflect that the phenomenon of convergence itself still is not fully understood and only in an emerging phase. "Strategic reaction to convergence" (strand 3) or the question of how to master "convergent products" (strand 4) are still questions that seem to be underresearched and thus need more attention in the future. Hence, to inspire future studies on methodological aspects and/or specific topics related to convergence, the following questions emerge from this special section:

### A. *Open Questions About Convergence Investigation Methods*

How can patent citation analysis be used to clearly demonstrate the phenomenon of technology convergence over time?

How does the analysis of technology convergence in urban innovation using the CPC scheme compare with similar research using the IPC scheme in other countries?

Can the findings of technology convergence research using the CPC scheme in the USA be compared with similar research in other countries using the IPC scheme?

How can advanced econometric models (e.g., spatial econometrics with common factors, the spatial dynamic model) be used to verify the spatial convergence of regional innovation?

How can the performance of classification algorithms (e.g., SVM, decision tree, random forest, gradient boosting, MLP, among others) be improved for anticipating technology convergence?

How does the comparison of different types of proximity indexes contribute to the development of an efficient method for anticipating technology convergence?

How does a cross-country analysis or a more specific focus on a particular step of the convergence process enhance our understanding of the fundamental role of industrial convergence during an industrial crisis?

How can future research be conducted to better understand the dynamics of industrial convergence through a quantitative study?

How can patent analysis limitations affect the study on convergence?

How can advanced NER and NLP techniques, such as BERT-based languages, be used to improve the analysis of technological convergence?

How can the growth pattern of emerging technologies in the C4ISTAR domain be studied and used for convergence and foresight?

How can alternative data sources, such as patent families, be used in conjunction with a patent-based approach to analyze industry convergence?

How can machine learning algorithms, such as topic modeling, be used to measure similarities in industry convergence?

How can deep-learning models be used for tasks, such as entity recognition and forecasting in the context of industry convergence?

What is the role of time in the convergence process, and how can process studies be used to better understand it?

### B. Open Questions About Convergence

What are the technical roots of patents that contribute to the growth of technology convergence and how has this changed over time?

How does market-driven convergence differ from the traditional linear process of convergence proposed by other studies?

How does digitization redefine the process of convergence in service industries?

What are the implications of market-driven convergence on industries that do not necessarily depend on technological advancements?

How does the analysis of regional innovation convergence in Eastern countries compare to other developing or developed Western countries?

How does the effect of high-, medium-, and low-tech industrial agglomeration differ on regional innovation convergence?

How does the heterogeneity of industries affect regional innovation convergence?

How do individual-level characteristics of inventing teams affect the search and recombination process, and in turn, the likelihood and speed of technological convergence?

How do open innovation practices and interactions with users and external partners during the technology development phase impact the technological convergence process?

How do purposeful policies to promote innovativeness in a specific field influence technological convergence?

How do the institutional origins of knowledge components recombined influence the likelihood and speed of technological convergence?

How does the distance between technological and geographical domains in which the knowledge components originate impact the likelihood and speed of technological convergence?

How do the relevance of the determinants of technological convergence change over time?

How do hybrid figures within business ecosystems contribute to the completion of convergence processes?

How can managers redesign jobs within organizational structures to better integrate skills required for technological advances like artificial intelligence and big data?

How does the integration of new technologies like Artificial Intelligence and big data affect the roles and responsibilities of professionals like physicians?

How does the convergence analysis change when it is based on startups and M&A?

How do changes in extra-technological considerations (e.g., geopolitics, policy making), impact the analysis of technological convergence?

How does technology impact preindustry convergence?

Are the early patentees of convergence also the winners later on, and what are the determinants that may favor or hinder their success?

How does convergence at the level of science and market or science and industry differ from technology and preindustry convergence?

How do the findings from the case of convergence between IT and CT in the ICT industry apply to other contexts and industries?

How does knowledge reuse and boundary spanning impact industry convergence and how does this relationship change over time?

How can researchers gain a deeper understanding of the convergence process and how can this knowledge be used to inform strategic decision-making?

What is the role of scientific convergence in industry convergence and how does it differ from other forms of convergence?

How have the convergence processes of communication technology developments impacted the media and communication industry?

How does the international environment impact convergence in different countries and regions?

What is the impact of convergence on learning and development, and how does this differ across different forms of convergence?

What factors facilitate or inhibit countries from converging economically, and how do they impact industrial convergence in developing countries?

What is the role of government in facilitating convergence and how do user adoption patterns differ between specialized and convergent products and services?

### C. Strand (1) Drivers and Patterns and Strand (2) Anticipation

Can the findings of technology convergence research using the CPC scheme in the USA be compared with similar research in other countries using the IPC scheme?

How can the performance of classification algorithms (e.g., SVM, decision tree, random forest, gradient boosting, MLP, among others) be improved for anticipating technology convergence?

How does the comparison of different types of proximity indexes contribute to the development of an efficient method for anticipating technology convergence?

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What is the impact of convergence on learning and development, and how does this differ across different forms of convergence?

How does technology impact preindustry convergence?

What is the role of scientific convergence in industry convergence and how does it differ from other forms of convergence?

### *D. Strand (3) Strategic Reactions and Strand (4) Convergent Products*

What are the implications of market-driven convergence on industries that do not necessarily depend on technological advancements?

How do open innovation practices and interactions with users and external partners during the technology development phase impact the technological convergence process?

How do individual-level characteristics of inventing teams affect the search and recombination process, and in turn, the likelihood and speed of technological convergence?

How do hybrid figures within business ecosystems contribute to the completion of convergence processes?

How can managers redesign jobs within organizational structures to better integrate skills required for technological advances like artificial intelligence and big data?

How does the integration of new technologies like Artificial Intelligence and big data affect the roles and responsibilities of professionals like physicians?

Are the early patentees of convergence also the winners later on, and what are the determinants that may favor or hinder their success?

What is the role of government in facilitating convergence and how do user adoption patterns differ between specialized and convergent products and services?

How can a deeper understanding of the convergence process be used to inform strategic decision-making?

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