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The Making of Convergence: Knowledge Reuse, Boundary Spanning, and the Formation of the ICT Industry

Fredrik Hacklin, Martin W. Wallin, Joakim Björkdahl, and Georg von Krogh

***Abstract*—While mastering technology and industry convergence are essential for firms across a growing number of industries, convergence is often rapid and abrupt, challenging firms to develop appropriate strategic responses. Focusing on the historical convergence between information technology and communication technology, we examine the microlevel behaviors of scientists initiating and driving convergence. Analyzing a bibliometric dataset of 257 641 scientific articles, we demonstrate how *industry convergence* manifests in a microlevel *scientific convergence*, preceding industry convergence by several decades. Our article contributes to the literature on convergence by developing new bibliometric measures for scientific convergence, and by contrasting microlevel behaviors that underpin convergence. Based on our findings, we offer a set of methods and strategies to assist managers in technology-based businesses with anticipating and responding to convergence in a timely manner.**

***Index Terms*—Bibliometric, convergence, information and communication technology (ICT), microfoundation, strategy, technology development.**

I. Introduction

MASTERING convergence is essential for survival in a growing number of industries. However, for many decision makers, the speed and abruptness of convergence often make it challenging to develop appropriate and timely strategic responses [1]–[8]. History is marked by firms failing to master convergence, sometimes leading to their ultimate demise. Nokia's cell phone business, for example, was quickly wiped out by Apple and Samsung, despite Nokia's explicit vision of converging the cellular phone with the PC [4], [9].

While firms seek to manage convergence as a result of firm-level strategic choices (e.g., [10]–[13]), recent research suggests that decision makers need to consider the more subtle individual-level forces at play that initiate and drive the phenomenon at large (e.g., [14], [15]). Similarly, the literature on strategy and organization commonly calls for "grassroot analysis" of complex phenomena, for example, how individual-level factors or "microfoundations" impact organizations, and how this interaction may come to shape emergent, collective, and organizational-level outcomes (see [16]–[19]). Indeed, a core thesis of this current study is that decision makers need to consider microlevel activities in order to deal with macrolevel changes such as industry convergence.

The convergence of industries is a hallmark of today's rapidly transforming business environment [7], [20], which is characterized by increased rivalry and an erosion of traditional sources of competitive advantage [1], [4], [12], [21]. In effect, there is growing consensus among scholars that convergence represents an important force shaping the business environment of many firms [3], [4], [7], [15], [21]. However, much of the existing literature either treat convergence as an empirical context to examine firm behavior rather than the phenomenon of prime interest (e.g., [13], [20], [22], [23]) or focuses specifically on the later-stage effects of convergence, for example, on its implications for the strategic positioning of firms (e.g., [24]–[26], [62]) or the formation of alliances and collaborations (e.g., [10], [12], [27]). To anticipate industry convergence, prior research has mainly examined patent data [7], [28], [34], and today there is limited understanding of the potential microlevel antecedents shaping past and current forces of industry convergence. Hence, we need to better understand "how convergence is being made" by specific contributions from individual actors within organizations. In this vein, scholars have called for a more comprehensive and multilevel approach that includes microlevel research exploring the early-stage antecedents to macrolevel convergence (e.g., [2], [20], [21], [29]). Such microlevel analysis could account for the actions of individual scientists and engineers who create and disseminate knowledge across scientific communities, sometimes long before these microlevel actions propagate into macrolevel industry convergence (e.g., [29]). However, despite these recent developments, the literature lacks a fine-grained analysis of the individual scientific behaviors that underpin industry convergence. This article is a response to these calls and contributes with a set of bibliometric measures, methods, and strategies to avoid convergence risks and to better sense and seize convergence opportunities.

In this study, we focus on the landmark case of information and communication technology (ICT) convergence and explore how ICT emerged from the convergence of knowledge in the

Manuscript received August 30, 2020; revised March 30, 2021 and May 17, 2021; accepted May 20, 2021. Review of this article was arranged by Department Editor F. Appio. *(Corresponding author: Fredrik Hacklin.)*

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Digital Object Identifier 10.1109/TEM.2021.3087365

domains of information technology (IT) and communication technology (CT). We analyze the publishing behaviors of individual-level actors in two scientific communities: the Association for Computing Machinery (ACM) representing IT, and the Institute of Electrical and Electronics Engineers (IEEE) representing CT. We construct a bibliometric dataset covering 257 641 scientific articles published within these two scientific communities from 1954 to 2009, an era characterized by significant change and upheaval in the global ICT industry (in other words, we collect data until about the time the iPhone had dethroned Nokia, forever transforming the ICT industry).

Our article offers a number of contributions to the literature. First, we demonstrate how *scientific convergence* is initiated by individual scientists long before the effects of *industry convergence* become a public topic. This is the case because most measures of technology convergence that could provide guidance to decision makers rest on patent and text analysis subsequent to publishing activity. Apart from challenges analyzing such data, these indicators rarely provide decision makers with the necessary time to prepare and act [7], [29].

Second, we highlight how *knowledge reuse,* defined as the application of previously created knowledge to solve a current problem (see, e.g., [30], [31]), and *boundary spanning*, defined as a set of activities performed by individuals to integrate knowledge across contexts (e.g., [32], [33]), are distinct microlevel behaviors underpinning convergence. Knowledge reuse and boundary spanning are important indicators and "warning signals" of technology convergence formation and industry convergence. Understanding convergence as a process driven by individuals creating and absorbing knowledge may also enable scholars to develop more effective theoretical frameworks for explaining and managing convergence.

Finally, based on our findings, we offer a set of strategies that can help managers anticipate and respond to convergence in a timely fashion.

II. Literature Review

Prior research has described how convergence emerges at different levels, resulting in scientific convergence, technological convergence, and industry convergence (e.g., [7], [34], [35]). In the following, we will briefly review the most important contributions from each. Specifically, we will identify a gap, signaling the need to further investigate scientific convergence and its individual-level origins as a way to anticipate industry convergence. This creates the backdrop of our study.

A. Technological Convergence

Technological convergence can be understood as an increasing overlap of distinct technological fields (e.g., [7], [36], [37]); it was originally identified in Rosenberg's [39, p. 18] seminal work on the U.S. machine tool industry. He observed that "the nature and the consequences of technological convergence" throughout an economy emerge through common types of processes.

> "It is because these processes and problems became common to the production of a wide range of disparate commodities that industries which were apparently unrelated from the point of view of the nature and uses of the final product became very closely related (technologically convergent) on a technological basis—for example, firearms, sewing machines, and bicycles." (see [39, p. 423]).

Thus, the convergence discourse over the past 30 years has often come from a technological perspective—specifically within the context of ICT [40]–[44]. For most of the period since Gambardella and Torrisi [45, p. 445] labeled the entire electronics industry "a quintessential example of technological convergence," there has been limited emphasis on the interplay between different levels of it [46], recently although several studies have provided more integrative, causal, and even procedural views of technology-driven convergence (e.g., [2], [5], [7], [20], [29], [36], [38], [47], [48], [50]–[53]). Earlier research has focused on issues such as the creation of technological overlap as a function of alliances and joint ventures [54], and as a variable impacting knowledge flows between companies [23] or within organizations [55]. It has also addressed the relationship between network resources and market entry on conditions of convergence [22]. However, research has not paid significant attention to individual-level behaviors driving convergence.

B. Industry Convergence

The convergence literature has long recognized that technological convergence is associated with industry-level changes (e.g., [7], [35], [56]). However, only recently scholars began focusing on industry-level outcomes [35], [57]–[59], and the implications for competition and firm strategy [9], [21], [22], [24], [26], [40], [60]–[62]. In these recent studies, convergence is not only about compounding previously distinct knowledge domains or technologies, it also encompasses a more broad-ranging phenomenon entailing "blurring boundaries" between "sectors of the economy" (see [63, p. 13]) or between "industries by converging value propositions, technologies, and markets" (see [64, p. 426]). For example, as CT and IT have become technologically related and intertwined, previously unrelated firms from different industry sectors have become direct competitors [4], [60]. Examples include the Alcatel–Lucent merger, and more recently, how TV cable and fiber network operators have begun offering phone subscriptions. Most prominently, Apple helped transform the ICT industry by merging the mobile phone with advanced computing capabilities.

While anecdotal evidence suggests industry convergence is an outcome of technological convergence, studying this mechanism has proven problematic: examining convergence as a focal phenomenon requires novel methods to "measure" technological boundaries. As Rosenkopf and Nerkar [65, p. 289] argue, "any such boundary between technologies is fuzzy and can evolve with time," which creates a need for static constructs that allow us to measure a dynamic phenomenon. As a result, capturing and measuring convergence requires a proper theoretical grounding as well as novel research designs. When aiming at empirically capturing boundary phenomena, scholars often build on existing categorizations provided by independent standardization bodies, such as patent classes or industry SIC codes (e.g., [5], [34], [47]). While these are both easily accessible and powerfully illustrate static boundaries, prudence is needed when studying dynamic phenomena such as the dissolving boundaries entailed in industry convergence. In such settings, existing categorizations evolve (see, e.g., [66]), often in response to structural changes that redefine the boundaries (e.g., SIC codes have increasingly adopted the convergence of IT and CT into ICT).

As a result of the current methodological challenges, our field's ability to connect the mechanisms of technology convergence with observations on industry convergence has remained modest. Prior literature thus remains rather limited in terms of offering advice to managers on attractive strategic responses to industry and technological convergence [46], [58]. Convergence often comes as a surprise to managers who are ill-prepared to respond before it is too late. Many firms report that they struggle to deal with convergence (e.g., [67]), which creates an imperative for researchers to explore new methods and techniques that help managers develop a more fine-grained understanding of the phenomenon, facilitating more informed and timely decision making [7].

C. Scientific Convergence

Against the challenges involved in examining the mechanisms of industry convergence, a recent stream of literature has sought to examine what is referred to as "scientific convergence." By studying the convergence phenomenon via a focus on the combination of scientific knowledge, a promising avenue has been identified allowing for early identification of emerging trends in technology and innovation (e.g., [29]). Scientific convergence refers to the increasing overlap between different scientific fields and is manifested through intensified cross-disciplinary scientific research [7], [36], [56]. Scientific convergence is therefore, different from technological convergence in that while the latter manifests in the technological artifacts (often captured as products and patents), the former is concerned with the underlying science in the abstract and less physical form (often captured through scientific publications of new discoveries, formulas, algorithms, and theories, e.g., [5], [29], [36], [38], [49]–[51], [56]). Prior studies have provided high-level illustrations of scientific convergence, for example in pharmaceuticals, nutraceuticals, and functional foods [34], [68], or in ICT [56]. The use of bibliometric data offers a novel way to analyze activity indicators [69]. By developing a bibliometric study analyzing citation patterns, Zhou *et al*. [29] suggest that scientific convergence starts from the knowledge flow between different scientific fields, which, as the flow gradually deepens, leads to the development of a new "research paradigm." Specifically, their results suggest that scientific convergence evolves through an incubation stage followed by a stable development stage. While this research is groundbreaking, the findings do not extend beyond the identification of distinct stages, and the authors thus call for more research to further unpack the mechanisms at play [29].

As it stands, scientific convergence can be regarded as "clearly defined in the literature and can be identified via structured indicators based on scientific publications" (see [7, p. 49]). Yet, the conceptual link between earlier stages of scientific convergence and industry convergence is still poorly understood. What are the antecedents of industry convergence, allowing decision makers to understand and perhaps anticipate whether science and technology convergence shape industry convergence? [7]. In this context, further research is needed in order to create tools to assess antecedents of industry convergence by gaining access to new datasets to provide additional rich insights [7]. For example, Zhou *et al.* [29] suggest further studies on semantic relationships (e.g., how a new knowledge base emerges) as well as social relationships (e.g., how scientific authors relate to each other) to develop a more fine-grained understanding of scientific convergence. Specifically, when going beyond the incubation stage, there is increasing evidence suggesting that socialization and collaboration across boundaries represent crucial catalysts for convergence to accelerate [27], [70], [72]–[74]. This calls for additional efforts to study scientific convergence by focusing on the behavior of individual scientific actors.

At the same time, a recent stream of literature focuses on the microfoundations of strategy [75]–[78], with the focal point of attention shifting toward the behavior of the individual actor. Research on microfoundations focuses on the influence of individual actions and interactions on the heterogeneity of organizations [75]. A claim in this work is that strategic choices cannot be fully understood without examining what decision makers and scientists are "doing". The same reasoning may apply to convergence as well. Albeit a problem of a strategic nature, convergence within ICT (such as in other sectors as well) has mainly been examined as company interactions or technological trajectories [34]. In such studies, it appears almost implicitly assumed that convergence takes place through organizations (e.g., "Apple entering the smartphone industry"), without considering more detailed levels of analysis of individual behavior as a root cause that shapes higher-level convergence. Here, a microfoundation perspective could offer complementary insights into the mechanisms behind industry convergence (see, e.g., [29]) by studying individuals working in firms, science labs, and universities, thereby offering the potential to gain a more comprehensive understanding of the phenomenon.

Against this backdrop, we apply new methods and techniques to explore how microlevel scientific convergence—one potential source of convergence between technologies and industries—can shed light on ICT convergence and subsequently inform decision makers in how to understand, drive, and respond to it. With the ICT industry as the quintessential example, we argue, this context allows for a sufficient level of historic perspective to engage in analysis on a deeper level.

III. Research Design

Conceptualizing today's ICT industry as the result of a convergence between two originating industries gives rise to studying what evolved in the IT industry and the CT industry separate from each other. From the perspective of scientific development, the IT industry can be seen as the commercialization of computer science know-how and technologies, resulting in personal computers, software, algorithms, and the like. In turn, the CT industry stands for products and solutions building on scientific advances in electrical engineering, such as signal transmission, wireless propagation, or frequency modulation.

A. Scientific Associations as Contextual Setting

The scientific basis for the ICT industry can be found in two professional associations: the ACM representing IT, and the IEEE representing CT (see Fig. 1.) The IEEE, the older of the two, traces its roots back to 1884 and the formation of the American Institute of Electrical Engineers (AIEE), set up to advance the electrical industry and its "Electrical Experts, Electricians, or Electrical Engineers" [79]. The institute was organized around the two leading electrical industries at that time—the power industry and the telegraph and telephone industry—as evidenced by its two vice-presidents, Thomas Edison and Alexander Graham Bell.

The ACM is the younger counterpart to the IEEE. It traces its roots to a founding meeting in 1947 and was "the logical outgrowth of increasing interest in computers" [80] following World War II. The original purpose of the ACM was "to advance the science, development, construction, and application of the new machinery for computing, reasoning, and other handling of information." Its original purpose in large part continues on today, although now it underscores its links to IT and engineering rather than to computing machines alone.

Similarly, the IEEE has reformulated its purpose into "serve(ing) professionals involved in all aspects of the electrical, electronic, and computing fields and related areas of science and technology that underlie modern civilization" [79]. That is, the two professional associations representing today's ICT industry were formed out of two distinctly different professions, but have over time become increasingly similar—thus mirroring the technological convergence that made the ICT industry. Indeed, today the ACM and the "IEEE Computer Society" organize a number of joint activities such as membership agreements and publication of journals (e.g., IEEE/ACM TRANSACTIONS ON NETWORKING).

By studying the scientific publishing activity in ACM and IEEE, we aim to uncover the microfoundations of convergence. Specifically, we use data repositories provided by ACM and IEEE, which contain all published academic journals and conference proceedings. We expect to observe how ACM and IEEE over time became increasingly interrelated.

The ICT industry provides a perfect setting for learning about convergence as nowadays it is a prime example of how industries change as a result of convergence [45]. This is not only because of the massive visibility of ICT in our daily lives—we have switched from landline phones to digital voice-over-IP, watch TV over the Internet, and buy "smart" phones from computer manufacturers—but also due to the maturity of this development. In some industries, convergence is still hovering at earlier stages (such as, e.g., nanobiotech or nutraceuticals in food-tech), whereas the convergence of IT and CT into ICT represents a relatively advanced stage of development, where many of the implications of convergence are undisputable.

B. Bibliometric Study

Based on data from ACM and IEEE, we built a bibliometric database consisting of all articles published in the respective society's journals from 1954 to 2009. We focused on this period for two reasons: First, the years around the turn of the millennium represent an era of massive change and upheaval in the global ICT industry [41], covering main events such as the digitization of telecommunications and the market penetration of handheld devices [81]. Having access to historic data as far back as the postwar era allowed us to explore antecedents such as the early stages of modern computing and communication technology. Second, we gained exclusive access to a rich dataset, with a truncation point in 2009 (about the time when industry convergence had started to yield significant effects, e.g., Apple dethroning Nokia). Data were accessed through the ISI Web of Knowledge by Thomson Reuters, where we were able to store all records in a locally operated relational database. For each article, we collected bibliometric data (such as author names, article title, name of the journal, time of publication, etc.). The resulting dataset consisted of 257 641 publications.

Association for Computing Machinery

- Association for Computing Machinery
- The world's first scientific and educational computing society
- 92'000 members
- 14 journal publications[1]
- Founded 1947

IEEE Celebrating 125 Years of Engineering the Future

- Institute of Electrical and Electronics Engineers
- International non-profit, professional organization for the advancement of technology related to electricity
- 395'000 members
- 110 journal publications[1]
- Founded 1963

Fig. 1. Research setting and context of this article.

Following the suggestion of Zhou *et al.* [29], we captured the level of semantic relationships (how the different knowledge bases relate to each other) as well as social relationships (how different authors interact). Conceptualizing both scientific communities as consisting of members that published articles in ACM and IEEE, respectively, we were able to measure scientific convergence in terms of *knowledge reuse* and *boundary spanning*.

Knowledge reuse is the application of previously created knowledge to solve a current problem (see, e.g., [30] and [31]). It captures the degree of underlying scientific similarity between communities, and in our setting, it is measured as previous articles being referred to in both the ACM and the IEEE fields (i.e., citation of the same article in both communities). Boundary spanning, in turn, is defined as a set of communication and coordination activities performed by individuals to integrate knowledge across contexts (e.g., [32], [33]). Here it is measured as one author crossing into the other community, being active in both the ACM and IEEE fields (i.e., publishing at least one article in both communities). Boundary spanning captures the degree to which individual scientists and engineers become "members" (albeit peripheral) of multiple scientific communities by publishing in both ACM and IEEE (see Fig. 2).

Scientific convergence is operationalized as the growth in similarity assessed through the *Jaccard index*, which measures similarity as the relative overlap (i.e., size of the intersection divided by the size of the union) between two sets. We construct two Jaccard indexes to capture scientific convergence (knowledge reuse and boundary spanning): one for the bibliographic coupling-based similarity between both fields (*JACREUSE*, i.e., ratio between the number of references commonly cited and all references during a given year), and a second for community similarity between both fields (*JACSPANNING*, i.e., ratio of the number of authors publishing in both fields and all authors active during a given year). We applied the Jaccard indexes on the bibliometric dataset, where each journal was classified as either belonging to electrical engineering (affiliated with IEEE) or computer science (affiliated with ACM).

IV. FINDINGS

Our findings on convergence are first presented through the core variables *JACREUSE* (knowledge reuse) and *JACSPANNING* (boundary spanning) and then through derivative measures to explore more fine-grained characteristics.

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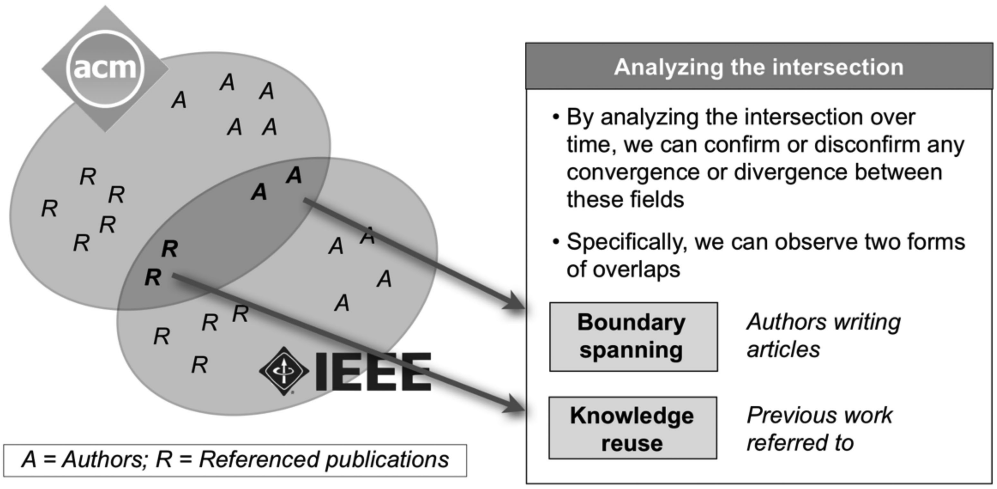

Fig. 2. Measuring scientific convergence using the Jaccard index.

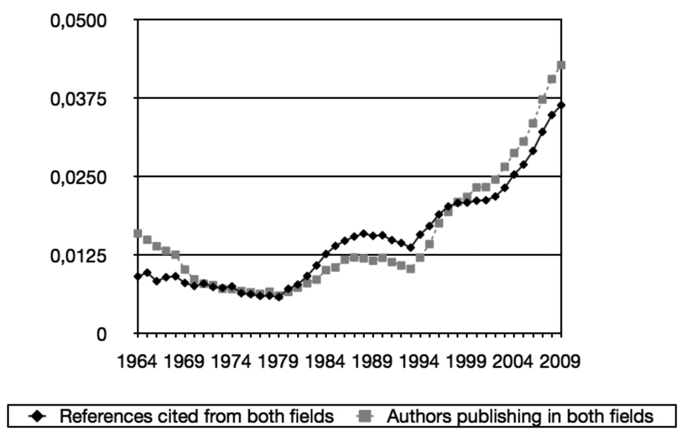

Fig. 3. Increase in boundary spanning between ACM and IEEE (*JACREUSE* versus *JACSPANNING*).

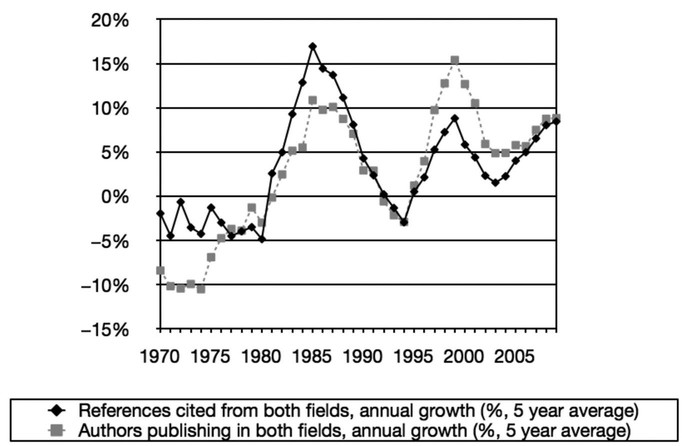

Fig. 4. Boundary spanning activity of individual scientists versus knowledge reuse (growth of *JACREUSE* versus growth of *JACSPANNING*, five years average).

A. Growth in Overlap of Scientific Activity Between ACM and IEEE

For both similarity measures, a clear increase in the overlap can be observed (see Fig. 3),[1] suggesting that there is an increasing trend toward knowledge reuse across the boundaries of ACM and IEEE and that there is an increasing number of individual researchers active in both fields simultaneously. In other words, the convergence of ICT as a baseline is reflected in the increasing overlap of the underlying scientific fields, starting toward the end of the 1970s.[2]

[1]As the Jaccard index is based on a ten-year sliding window, the time of our first observation increases by ten years, i.e., from 1954 to 1964.

[2]Even though the scope of activities between ACM and IEEE have expanded over time, more closely aligning the communities formally, this does not seem to impact the overall trend. Even though these results may implicitly suffer from the problem of dynamic categories, an additional correction of these would strengthen the results observed here.

B. Waves of Reference Reuse and Author Activity

Extending the analysis, we find that knowledge reuse and boundary spanning play slightly different roles in ICT convergence. Examining the rate of annual growth of both Jaccard indexes, we observe two consecutive phases of strong growth, i.e., between the early 1980s and early 1990s, as well as between the late 1990s and mid-2000s (see Fig. 4). In both phases, the similarity reaches relative growth rates above 15% relative to the previous year (a five-year sliding average, therefore the first observation starts at 1970). However, these two phases differ: during the first phase, the bibliographic coupling similarity shows stronger growth, whereas in the latter phase, the community grows stronger (see Fig. 4), driven by authors' activity of crossing disciplinary boundaries and engaging in collaborative publications.

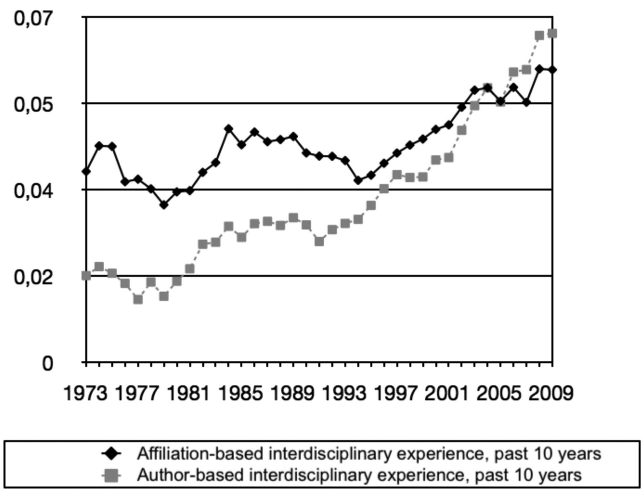

Fig. 5. Affiliation-based (*IAFAVG*) versus author-based interdisciplinary experience (*IAUAVG*).

C. Interdisciplinary Experience: Individuals Versus Institutions

Having established how individual scientists contribute to convergence, we next turn our attention to how scientists are institutionally embedded. We find that in the early years of ICT convergence, institutional embeddedness is crucial for individual scientists to contribute to convergence. It would appear that strong institutions, such as universities, are needed for individual scientists to cross disciplinary boundaries, providing stability and conditions supportive of experimentation and risk-taking. We explore this institutional embeddedness through organizational affiliation. Specifically, we develop two new measures to compare and contrast how individuals versus institutions contribute to early-stage convergence. We first calculate two intermediate measures that examine the degree of "interdisciplinary experience" embodied in a paper. For a focal paper, we first calculate the ratio between the authors' number of prior publications in IEEE journals and the number of prior publications in ACM journals (author-based intermediate measure), as well as the ratio of the number of prior occurrences of the authors' affiliation in IEEE and the number of prior occurrences in ACM (affiliation-based intermediate measures). We then aggregated onto the level of the entire sample by computing an "average of averages" to arrive at our final measures of *IAUAVG(t)*, representing the aggregate convergence work done by individuals during the past ten years up to year *t*, and *IAFAVG(t)*, representing the aggregate convergence work done by institutions during the past ten years up to year *t* (see Fig. 5). For a detailed explanation of how the measures were calculated, see the Appendix.

However, in the earlier stages of the convergence clear patterns with regard to organizations dominating the interdisciplinary experience (institutions contributing more to convergence across boundaries than their affiliated individual authors, i.e., $IAFAVG(t) > IAUAVG(t)$) could be observed, it seems that individual scientists are catching up toward the end of the 2000s and become more prominent as a mechanism around 2005 (authors exhibiting higher interdisciplinary experience than institutions/affiliations, i.e., $IAUAVG(t) > IAFAVG(t)$).

D. Citation Patterns in Response to Contribution to Convergence

Focusing on individual papers, we are able to demonstrate that the convergence phenomenon is not isolated from other scientific progress. On the contrary, papers that contribute to convergence are highly cited in the wider literature, suggesting convergence was related to core scientific problems during the time of observation. To explore these issues, we took the following steps: The convergence ratio CR*(P)* was introduced in order to attribute an individual paper's contribution to convergence (for a detailed definition, see the Appendix). When the CR*(P)* equals 1, the article recombines knowledge to a maximum amount by combing a proportional quantity from the ACM and IEEE fields (i.e., proportional to the size of the respective field). This allowed the contrasting of contribution to convergence and citation counts. Fig. 6 illustrates how the average number of citations per paper develops over time, and how this differs according to the papers' contribution to convergence (charts "0–3" show a split over intervals of CR*(P)* with increasing value; chart "4" shows the case of CR*(P)* at zero level). Two observations can be made: First, papers with higher CR*(P)* value (charts "2" and "3" in Fig. 6) demonstrate up to twice as many average citation counts as papers with a lower CR*(P)* value (charts "0" and "1"). Therefore, papers that contribute to ICT convergence seem to be more influential (in terms of citations) than those that do not. Second, the citation activity, particularly for papers with higher CR*(P)* values (charts "2" and "3"), seems to peak around the late 1970s. This gives rise to a phase of very influential knowledge creation right before and after 1980, which other authors later built upon.

E. Team Size of Influential Papers

To further explore scientific-individual behaviors, we examined the role of teamwork (i.e., coauthoring). Interestingly, we found that larger teams to a lesser degree are associated with contributions to convergence. This points to challenges within author teams to integrate knowledge across disciplinary boundaries. To arrive at this finding, we juxtaposed team size (i.e., number of coauthors) and the contribution to convergence at the level of a paper (i.e., CR*(P)*). Fig. 7 shows the average CR*(P)* value across all published papers for each team size censored between 2 and 10. It is immediately clear that in terms of pure arithmetic average, papers with a higher degree of contribution to the overlap between ACM and IEEE (i.e., higher contribution to convergence) seem to be associated with smaller teams, perhaps peaking at a team size of three.

F. Subfields Leading the Contribution to Convergence

Finally, we find that scientists link their convergence papers to broad categories of basic science. The bibliometric dataset offered access to a variety of additional information attributable to each published paper, as well as to each underlying publication outlet (i.e., a journal or a conference of ACM or IEEE, respectively). Specifically, each publication outlet was associated with one subject category (see Table I). Similar to the previous section, drawing on mean values of CR*(P)* allowed a simple insight into which subject categories are found under the highest

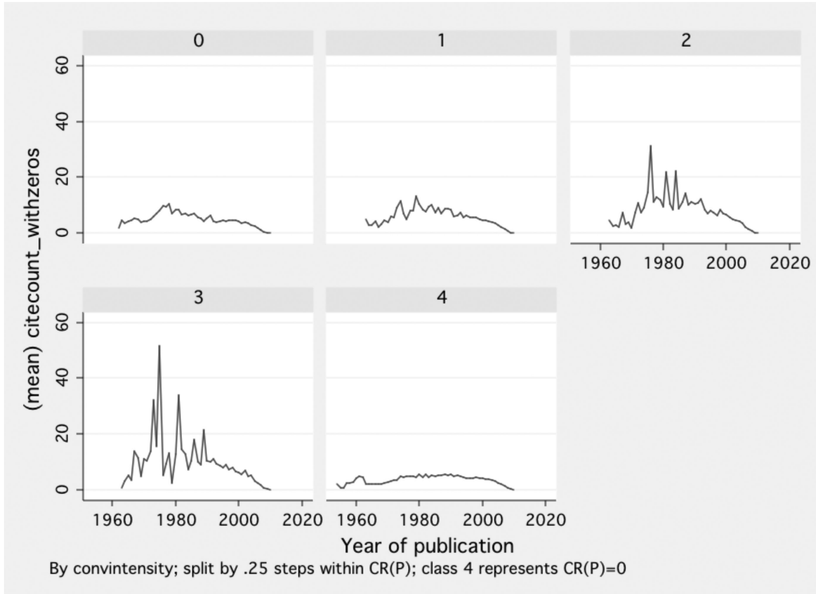

Fig. 6. Citation counts over time, by different degrees of convergence intensity (chart "0": $0 < \mathrm{CR}(P) \leq 0.25$; chart "1": $0.25 < \mathrm{CR}(P) \leq 0.5$; chart "2": $0.5 < \mathrm{CR}(P) \leq 0.75$; chart "3": $0.75 < \mathrm{CR}(P) \leq 1$; chart "4": $\mathrm{CR}(P) = 0$).

TABLE I
SUBJECT CATEGORIES

ACOUSTICS	GEOGRAPHY, PHYSICAL
AEROSPACE ENGINEERING & TECHNOLOGY	HISTORY & PHILOSOPHY OF SCIENCE
AUTOMATION & CONTROL SYSTEMS	IMAGING SCIENCE & PHOTOGRAPHIC TECHNOLOGY
BIOCHEMICAL RESEARCH METHODS	INSTRUMENTS & INSTRUMENTATION
BUSINESS	MANAGEMENT
COMMUNICATION	MATERIALS SCIENCE
COMPUTER APPLICATIONS & CYBERNETICS	MATERIALS SCIENCE, BIOMATERIALS
COMPUTER SCIENCE, ARTIFICIAL INTELLIGENCE	MATERIALS SCIENCE, MULTIDISCIPLINARY
COMPUTER SCIENCE, CYBERNETICS	MATHEMATICAL & COMPUTATIONAL BIOLOGY
COMPUTER SCIENCE, HARDWARE & ARCHITECTURE	MATHEMATICS, APPLIED
COMPUTER SCIENCE, INFORMATION SYSTEMS	MATHEMATICS, INTERDISCIPLINARY APPLICATIONS
COMPUTER SCIENCE, INTERDISCIPLINARY APPLICATIONS	MEDICAL INFORMATICS
COMPUTER SCIENCE, SOFTWARE ENGINEERING	NANOSCIENCE & NANOTECHNOLOGY
COMPUTER SCIENCE, SOFTWARE, GRAPHICS, PROGRAMMING	NUCLEAR SCIENCE & TECHNOLOGY
COMPUTER SCIENCE, THEORY & METHODS	OCEANOGRAPHY
EDUCATION, SCIENTIFIC DISCIPLINES	OPTICS
ENERGY & FUELS	PHYSICS, APPLIED
ENGINEERING	PHYSICS, CONDENSED MATTER
ENGINEERING, AEROSPACE	PHYSICS, FLUIDS & PLASMAS
ENGINEERING, BIOMEDICAL	RADIOLOGY & NUCLEAR MEDICINE
ENGINEERING, CIVIL	RADIOLOGY, NUCLEAR MEDICINE & MEDICAL IMAGING
ENGINEERING, ELECTRICAL & ELECTRONIC	REHABILITATION
ENGINEERING, INDUSTRIAL	REMOTE SENSING
ENGINEERING, MANUFACTURING	ROBOTICS
ENGINEERING, MARINE	ROBOTICS & AUTOMATIC CONTROL
ENGINEERING, MECHANICAL	STATISTICS & PROBABILITY
ENGINEERING, MULTIDISCIPLINARY	TELECOMMUNICATIONS
ENGINEERING, OCEAN	TRANSPORTATION
ERGONOMICS	TRANSPORTATION SCIENCE & TECHNOLOGY
GEOCHEMISTRY & GEOPHYSICS	

Source: ISI Web of Knowledge, Thomson Reuters.

contribution to convergence. The three top-scoring subject categories were: #1 "engineering, electrical and electronic" (mean $\mathrm{CR}(P) = 0.93$); #2 "physics, applied" (mean $\mathrm{CR}(P) = 0.37$); and #3 "optics" (mean $\mathrm{CR}(P) = 0.10$). Clearly, the top-scoring categories do not exhibit any largely specialized technological subdomain but instead are represented through broadly defined domains of basic science.

V. Discussion and Implications for Managers

In the following, we discuss our empirical results and offer ideas for how they can contribute to the literature on convergence. We then turn to implications for managers and develop a set of strategies for managing convergence. Finally, we discuss limitations and the potential for future research.

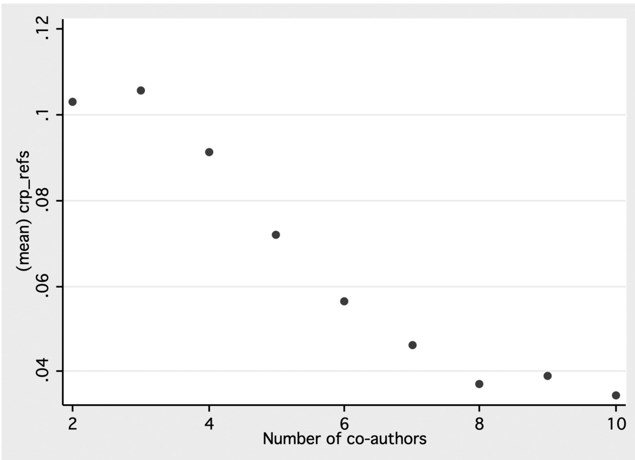

Fig. 7. Average convergence ratio over author team size.

A. Key Contributions to the Convergence Literature

This article explored the microfoundations of early-stage convergence in the ICT industry, drawing on a bibliometric dataset. Our literature review uncovered 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. We developed 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. In other words, scientists began cocreating knowledge across ACM–IEEE boundaries much earlier than the corresponding industry convergence and its associated firm-level challenges. Moreover, there was an increasing number of individual researchers active in both fields simultaneously (see Fig. 7). By comparing the relative growth of the Jaccard indexes over time (overlap), we concluded that knowledge reuse and boundary spanning do not seem to fully correlate, but rather emerge sequentially. 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 (see Fig. 4). This suggests that early-stage ICT convergence happened in two consecutive waves, and is associated with two different microlevel behaviors—first by scientists "looking," and second by "walking," across different fields. At the same time, our results underscore that larger author teams struggle to contribute to convergence.

We contribute to prior research examining convergence in three ways. First, our findings contribute to the understanding of how microlevel convergence mechanisms develop and change over time, which prior research has called for (e.g., [7], [12], [81]). The convergence that is initiated by individual scientists is in line with the few studies conducted on scientific convergence and on convergence outside the field of ICT (e.g., Zhou *et al.* [29] in the field of bioinformatics). These findings are important in the rapidly changing environment in which technological and industry boundaries erode and create novel competitive plays, and there are calls for the individual agency to master technology and industry convergence (see, e.g., [82], [83] for similar arguments in the literature on open innovation). Against this backdrop, we believe our study offers more nuanced insights on "how convergence is made".

Second, scholars have called for research to explore how new knowledge bases emerge and how scientific authors relate to each other as a way to develop a more fine-grained understanding of scientific convergence (e.g., [29]). We contribute to the literature on convergence by highlighting how knowledge reuse and boundary spanning are two distinct microlevel behaviors underpinning convergence. This is important for two reasons. First, if we start to understand convergence as a process shaped not only by organizations but also by individuals creating and reusing knowledge, researchers can develop more effective frameworks for explaining and assessing convergence. Second, we can move beyond the frequently proposed early indicator of technology convergence to anticipate industry convergence. The use of patent and text data has been shown to involve biases and difficulties realizing and acting in a timely manner [7], [29]. Researchers have long tried to find more suitable measures to anticipate industry convergence (e.g., [51]). We believe the focus on boundary spanning and knowledge reuse are suitable measures to include when attempting to anticipate industry convergence, at least in the context of ICT. Indeed, our findings underscore that firms are part of an ecosystem consisting of multiple stakeholders that may reach beyond firm boundaries in creating knowledge. As illustrated in the case of ICT, the convergence of industries can hardly be precipitated through firms' deliberate actions but evolves through a relatively obscure process. Hence, it seems expedient to develop early microlevel indicators of convergence. At the same time, we need to consider industry and technology idiosyncrasy—while our findings may hold for ICT, it may be different in other cases, such as artificial intelligence, where companies often are in command and sometimes limit the agency of individual scientists, for example in terms of publishing results.

Third, albeit building on the previous, we extend our methodological repertoire of studying convergence. By formalizing and developing an operationalization of our key constructs (knowledge reuse and boundary spanning), we offer novel tools and measures applicable for analyzing large bibliometric datasets. Specifically, our key variables—the convergence ratio, author, and affiliation interdisciplinary ratio (CR, IAU, and IAF, see the Appendix)—have proven easily implementable, yet powerful instruments to capture the emerging overlap between two previously disparate communities.

B. Nurturing Individual Agency

Our results suggest that the convergence of the ICT industry can be traced back to early developments in interactive behavior among individual scientists and engineers. This stands in contrast to the common belief that changes in regulation during the 1990s were largely responsible for triggering ICT convergence (see, e.g., [71]). Our results show that scientific activity started to pick up during the early 1980s, but that it was present long before. Hence, one can argue that deliberate managerial activity may have reinforced convergence at later stages, but that such activity was made possible by engineers and scientists operating within and between the ACM and IEEE scientific communities.

While in earlier phases, the convergence was driven through mutual knowledge reuse, it was at later stages driven by the engagement into boundary-spanning activities (see Fig. 3). A

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number of issues can be teased out from these observations. Certainly, 1) it points to the importance of the availability of information to enable knowledge reuse in the early phases of technological convergence; 2) that initially, entrepreneurial early movers (or "cross-boundary disruptors," see [1]) might be critical to initiating technological convergence; and 3) it might reflect new programs and policies that encourage collaboration once technological convergence hits the policymaker's radar screen. As a consequence, firms aiming to achieve cross-industry breakthroughs may need to remain "patient and poised." Focusing on involving individuals with high levels of curiosity and ambition to learn may turn out to be a productive approach to propelling convergence.

As indicated by our results, whereas the convergence in ICT was initially associated with institutions employing collaborating scientists, a few dominant and recurring individuals spread across more institutions were observable in the later stages (see Fig. 4). Here, our study plants the seeds for more data-driven managerial decision making. We put forward a number of straightforward tools to measure convergence. This can help managers to better grasp convergence, bringing it from the abstract to the observable. In a world of the increasing availability of data and diminishing processing costs, microlevel bibliometric tools can become an essential part of any technology manager's analytical toolbox.

Future research should examine the relationship between individual scientists and the institutional contexts, focusing on funding conditions and schemes, infrastructure support, talent development, career choices, institutional norms, etc. For example, with ICT early-stage research funding was likely extensive and critical (e.g., in material science and experimental physics), and funding agencies may have been willing to accept considerable risk by supporting scientists' early visions of the anticipated benefits of crossing scientific boundaries.

C. Creating Lighthouses With Properly Sized Teams

Further, our observations related to citation patterns (see Fig. 5) have implications for understanding how innovation underlying technological convergence is diffused. Recall that publications that to a higher degree contribute to convergence are cited more frequently. Thus, this might imply that the spill-over of knowledge across technological fields is initiated by influential "lighthouse" publications, but then further accelerated through knowledge reuse in the scientific community. Moreover, the citations peak around the late 1970s, which may imply the existence of a culmination point in the convergence between the fields during which many highly influential convergence-intense publications were appearing.

In turn, the findings related to team sizes of influential papers (see Fig. 6) offer important insights to the organization of teams for cross-disciplinary knowledge work. However, larger teams tend to increase the likelihood of having several complementary areas of expertise present, the high-level findings of this analysis suggest that smaller teams have the highest impact on integrating knowledge across technological fields. Likely, as teams grow larger in size, coordination costs start to act to their disadvantage, which turns particularly detrimental when tasked with the challenge of recombining technological knowledge across different fields.

D. Leaving Space for Creating the Foundation

Finally, the snapshot of top-scoring subject categories (see Table I) provides somewhat counterintuitive findings as to what type of scientific behavior is driving technological convergence. Given the role of and impact on firms in later stages, one may expect technological convergence to be driven by applied, rather than basic, research. However, this may not be the case. Consider, for example, that applied physics and optics were the subfields with the second- and third-highest degrees of association with convergence. This insight largely contradicts the conventional logic that assumes deliberate market-oriented R&D activity is the main force behind convergence. Instead, from a policymaking perspective, this emphasizes the critical importance of basic research as a necessary enabler for technological convergence to emerge in the first place.

In other words, in the case of ICT convergence, scientists do not seem to be lagging behind firms, and there is no real need to get them out of the ivory tower. In fact, according to these findings, they may never have been locked there in the first place. Scientists were spanning disciplinary boundaries long before—and firms need to learn early on how to absorb information, knowledge, and the most productive opportunities. How? A good start is to listen to what scientists say to each other across disciplinary boundaries.

E. Limitations and Future Research

Our study does not come without limitations. We analyzed the case of convergence between IT and CT. The journals analyzed were ACM and IEEE journals. Further research is needed to show if and how our findings are applicable to other contexts beyond the ICT industry. This is not only important for developing a better understanding of convergence, e.g., in terms of whether convergence is a linear and sequential process involving scientific, technology, and industry convergence, as argued for in prior research (e.g., [7]), but also for how scientific convergence is a useful and complementary indicator of industry convergence—as has been shown in the context of ICT. In our study, we found how knowledge reuse and boundary spanning are microlevel behaviors associated with convergence. We believe there is a need for further research to open up the black box by analyzing and explaining how the relationship between these activities, technology formation, and industry convergence unfold over time. In particular, we see a need for taking time more seriously by conducting process studies of convergence, involving activities and events of scientific, technology, and industry convergence. This is important because it would give researchers a much deeper and richer understanding of the convergence process and could give business leaders better tools for their strategizing activities.

APPENDIX

Interdisciplinarity ratio

We construct a variable to capture the interdisciplinary experience represented in a paper. Specifically, we measure the ratio of prior publications during the last 10 years, both for authors listed in a given paper as well as the affiliations represented in the paper.

For a focal paper P, we define for each author listed in the paper the author interdisciplinarity ratio IAU as

$$\mathrm{IAU} = \frac{\text{no. of author} - \text{publications in IEEE}}{\text{no. of author} - \text{publications in ACM}} \text{ with IAU : } = 1/\mathrm{IAU} \text{ if } \mathrm{IAU} > 1.$$

Similarly, for each affiliation listed in the paper, we define the affiliation interdisciplinarity ratio IAF as

$$\mathrm{IAF} = \frac{\text{no. of affiliation} - \text{publications in IEEE}}{\text{no. of affiliation} - \text{publications in ACM}} \text{ with IAF: } = 1/\mathrm{IAF} \text{ if } \mathrm{IAF} > 1$$

TABLE II
LIST OF JOURNALS INCLUDED IN THE SAMPLE

ACM
ACM COMPUTING SURVEYS
ACM SIGPLAN NOTICES
ACM TRANSACTIONS ON COMPUTATIONAL LOGIC
ACM TRANSACTIONS ON COMPUTER SYSTEMS
ACM TRANSACTIONS ON DATABASE SYSTEMS
ACM TRANSACTIONS ON DESIGN AUTOMATION OF ELECTRONIC SYSTEMS
ACM TRANSACTIONS ON GRAPHICS
ACM TRANSACTIONS ON INFORMATION SYSTEMS
ACM TRANSACTIONS ON MATHEMATICAL SOFTWARE
ACM TRANSACTIONS ON MODELING AND COMPUTER SIMULATION
ACM TRANSACTIONS ON MULTIMEDIA COMPUTING COMMUNICATIONS AND APPLICATIONS
ACM TRANSACTIONS ON PROGRAMMING LANGUAGES AND SYSTEMS
ACM TRANSACTIONS ON SOFTWARE ENGINEERING AND METHODOLOGY
JOURNAL OF THE ACM
IEEE
IEEE AEROSPACE AND ELECTRONIC SYSTEMS MAGAZINE
IEEE ANNALS OF THE HISTORY OF COMPUTING
IEEE ANTENNAS AND PROPAGATION MAGAZINE
IEEE ANTENNAS AND WIRELESS PROPAGATION LETTERS
IEEE CIRCUITS & DEVICES
IEEE COMMUNICATIONS LETTERS
IEEE COMMUNICATIONS MAGAZINE
IEEE COMPUTATIONAL INTELLIGENCE MAGAZINE
IEEE COMPUTER GRAPHICS AND APPLICATIONS
IEEE CONTROL SYSTEMS MAGAZINE
IEEE DESIGN & TEST OF COMPUTERS
IEEE ELECTRICAL INSULATION MAGAZINE
IEEE ELECTRON DEVICE LETTERS
IEEE ENGINEERING IN MEDICINE AND BIOLOGY MAGAZINE
IEEE GEOSCIENCE AND REMOTE SENSING LETTERS
IEEE INDUSTRY APPLICATIONS MAGAZINE
IEEE INSTRUMENTATION & MEASUREMENT MAGAZINE
IEEE INTELLIGENT SYSTEMS
IEEE INTERNET COMPUTING
IEEE JOURNAL OF OCEANIC ENGINEERING
IEEE JOURNAL OF QUANTUM ELECTRONICS
IEEE JOURNAL OF SELECTED TOPICS IN QUANTUM ELECTRONICS
IEEE JOURNAL OF SOLID-STATE CIRCUITS
IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS
IEEE MICRO
IEEE MICROWAVE AND WIRELESS COMPONENTS LETTERS
IEEE MICROWAVE MAGAZINE
IEEE MULTIMEDIA
IEEE NETWORK
IEEE PERVASIVE COMPUTING
IEEE PHOTONICS TECHNOLOGY LETTERS
IEEE ROBOTICS & AUTOMATION MAGAZINE
IEEE SECURITY & PRIVACY
IEEE SENSORS JOURNAL
IEEE SIGNAL PROCESSING LETTERS
IEEE SIGNAL PROCESSING MAGAZINE
IEEE SOFTWARE
IEEE SPECTRUM
IEEE TECHNOLOGY AND SOCIETY MAGAZINE
IEEE TRANSACTIONS ON ADVANCED PACKAGING
IEEE TRANSACTIONS ON AEROSPACE AND ELECTRONIC SYSTEMS
IEEE TRANSACTIONS ON ANTENNAS AND PROPAGATION
IEEE TRANSACTIONS ON APPLIED SUPERCONDUCTIVITY
IEEE TRANSACTIONS ON AUDIO SPEECH AND LANGUAGE PROCESSING
IEEE TRANSACTIONS ON AUTOMATIC CONTROL
IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING
IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING
IEEE TRANSACTIONS ON BROADCASTING

LIST OF JOURNALS INCLUDED IN THE SAMPLE

IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS FOR VIDEO TECHNOLOGY
IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS I-REGULAR PAPERS
IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS II-EXPRESS BRIEFS
IEEE TRANSACTIONS ON COMMUNICATIONS
IEEE TRANSACTIONS ON COMPONENTS AND PACKAGING TECHNOLOGIES
IEEE TRANSACTIONS ON COMPUTER-AIDED DESIGN OF INTEGRATED CIRCUITS AND SYSTEMS
IEEE TRANSACTIONS ON COMPUTERS
IEEE TRANSACTIONS ON CONSUMER ELECTRONICS
IEEE TRANSACTIONS ON CONTROL SYSTEMS TECHNOLOGY
IEEE TRANSACTIONS ON DEPENDABLE AND SECURE COMPUTING
IEEE TRANSACTIONS ON DEVICE AND MATERIALS RELIABILITY
IEEE TRANSACTIONS ON DIELECTRICS AND ELECTRICAL INSULATION
IEEE TRANSACTIONS ON EDUCATION
IEEE TRANSACTIONS ON ELECTROMAGNETIC COMPATIBILITY
IEEE TRANSACTIONS ON ELECTRON DEVICES
IEEE TRANSACTIONS ON ELECTRONICS PACKAGING MANUFACTURING
IEEE TRANSACTIONS ON ENERGY CONVERSION
IEEE TRANSACTIONS ON ENGINEERING MANAGEMENT
IEEE TRANSACTIONS ON EVOLUTIONARY COMPUTATION
IEEE TRANSACTIONS ON FUZZY SYSTEMS
IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING
IEEE TRANSACTIONS ON IMAGE PROCESSING
IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS
IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS
IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS
IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY
IEEE TRANSACTIONS ON INFORMATION TECHNOLOGY IN BIOMEDICINE
IEEE TRANSACTIONS ON INFORMATION THEORY
IEEE TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENT
IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS
IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING
IEEE TRANSACTIONS ON MAGNETICS
IEEE TRANSACTIONS ON MEDICAL IMAGING
IEEE TRANSACTIONS ON MICROWAVE THEORY AND TECHNIQUES
IEEE TRANSACTIONS ON MOBILE COMPUTING
IEEE TRANSACTIONS ON MULTIMEDIA
IEEE TRANSACTIONS ON NANOBIOSCIENCE
IEEE TRANSACTIONS ON NANOTECHNOLOGY
IEEE TRANSACTIONS ON NEURAL NETWORKS
IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING
IEEE TRANSACTIONS ON NUCLEAR SCIENCE
IEEE TRANSACTIONS ON PARALLEL AND DISTRIBUTED SYSTEMS
IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE
IEEE TRANSACTIONS ON PLASMA SCIENCE
IEEE TRANSACTIONS ON POWER DELIVERY
IEEE TRANSACTIONS ON POWER ELECTRONICS
IEEE TRANSACTIONS ON POWER SYSTEMS
IEEE TRANSACTIONS ON RELIABILITY
IEEE TRANSACTIONS ON ROBOTICS
IEEE TRANSACTIONS ON SEMICONDUCTOR MANUFACTURING
IEEE TRANSACTIONS ON SIGNAL PROCESSING
IEEE TRANSACTIONS ON SOFTWARE ENGINEERING
IEEE TRANSACTIONS ON SYSTEMS MAN AND CYBERNETICS PART A-SYSTEMS AND HUMANS
IEEE TRANSACTIONS ON SYSTEMS MAN AND CYBERNETICS PART B-CYBERNETICS
IEEE TRANSACTIONS ON SYSTEMS MAN AND CYBERNETICS PART C-APPLICATIONS AND REVIEWS
IEEE TRANSACTIONS ON ULTRASONICS FERROELECTRICS AND FREQUENCY CONTROL
IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY
IEEE TRANSACTIONS ON VERY LARGE SCALE INTEGRATION (VLSI) SYSTEMS
IEEE TRANSACTIONS ON VISUALIZATION AND COMPUTER GRAPHICS
IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS
IEEE WIRELESS COMMUNICATIONS
PROCEEDINGS OF THE IEEE

We subsequently aggregate both measures onto a per paper level by constructing the vectors *IAUV(P)* and *IAFV(P)* as well as computing their means *IAUVAVG(P)* and *IAFVAVG(P)* as follows:

IAUV(P) $= (IAU_1, IAU_2, IAU_3, \ldots IAU_n)$ for all n authors listed in the paper;

IAFV(P) $= (IAF_1, IAF_2, IAF_3, \ldots IAF_m)$ for all m affiliations listed in the paper;

IAUVAVG(P) $= (IAU_1 + IAU_2 + IAU_3 + \ldots + IAU_n) / n$ for all n authors listed in the paper;

IAFVAVG(P) $= (IAF_1 + IAF_2 + IAF_3 + \ldots + IAF_m) / m$ for all m affiliations listed in the paper.

Finally, we compute the average of all papers of the sample *IAUAVG(t)* and *IAFAVG(t)* for each year t

$$IAUAVG\,(t) = \frac{\sum_{p=1}^{s} IAUVAVG\,(p)}{s}$$

with s papers published during year t;

$$IAFAVG\,(t) = \frac{\sum_{p=1}^{s} IAFVAVG\,(p)}{s}$$

with s papers published during year t.

Convergence ratio (CR)

We construct a variable to capture the knowledge recombination for a scientific article from references to the knowledge fields IT and CT. Hence, we define $\mathrm{CR}(P)$ for a focal paper *P* as a continuous variable between 0 and 1 based on the balance of two Jaccard indexes

$$\mathrm{CR}\,(P): \;= \left\lfloor \frac{J\,(P, IT)}{J\,(P, CT)} \right\rfloor \;= \left\lfloor \frac{|(P \cap IT)|}{|(P \cup IT)|} \frac{|(P \cup CT)|}{|(P \cap CT)|} \right\rfloor$$

with the Jaccard operator

$$J\;(A, B) = \frac{|(\mathrm{A} \cap \mathrm{B})|}{|(\mathrm{A} \cup \mathrm{B})|}$$

and with a normalizing function

$$\lfloor x \rfloor := \begin{cases} 1/x, & x > 1 \\ x, & \text{otherwise} \end{cases}.$$

The first Jaccard operator captures the similarity of the list of scientific articles cited by the focal article with the list of all scientific articles published in IT journals and conferences (i.e., the IT field). Similarly, the second Jaccard index captures the similarity of the list of articles cited by the same focal article with the list of all articles published in CT journals and conferences (i.e., the CT field). Consequently, if the CR of a scientific article equals 1, the article recombines knowledge to a maximum extent, as it combines a proportional quantity of knowledge from both technological fields proportional to the size of the domains. In contrast, if the CR of an article equals 0, then it has a zero overlap with at least one of the two knowledge fields, which means that it builds entirely on knowledge from one field only.

For a list of journals included in the sample, see Table II.

ACKNOWLEDGMENT

The authors gratefully acknowledge the research assistance of E. Aksüyek, J. Röder and M. Mösli, as well as the generous support by the MTEC Foundation and the ETH Zurich Web of Science Core Collection team. All errors remain their own.

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