TECHNOLOGY EMERGENCE AS A STRUCTURING PROCESS: A COMPLEXITY THEORY PERSPECTIVE ON BLOCKCHAIN

Elona Marku
University of Cagliari
Via Sant' Ignazio 74 – 09123
Cagliari, Italy
elona.marku@unica.it

Maria Chiara Di Guardo
University of Cagliari
Via Sant' Ignazio 74 – 09123
Cagliari, Italy
diguardo@unica.it

Gerardo Patriotta
Warwick Business School
University of Warwick
Coventry CV4 7AL, UK
Gerardo.Patriotta@wbs.ac.uk

David Allen*
Neeley School of Business
Texas Christian University
Fort Worth, TX 76129, USA
&
Warwick Business School
University of Warwick
david.allen@tcu.edu

Acknowledgments: The authors wish to express gratitude to Editor Gokhan Ertug and two anonymous reviewers for their insightful feedback throughout the review process. We are also thankful to Silvio Piredda and Paolo Mattana for their valuable contribution to research assistance and model development. Special thanks to Elisa Operti, Riccardo Fini, and Ryan Krause for their insightful feedback during the manuscript's final review stage. This study was funded by the European Union - NextGenerationEU, in the framework of the GRINS -Growing Resilient, INclusive and Sustainable project (CUP F53C22000760007). The views and opinions expressed are solely those of the authors and do not necessarily reflect those of the European Union, nor can the European Union be held responsible for them.
**** Corresponding author***

Technology emergence as a structuring process:

A complexity theory perspective on blockchain

ABSTRACT

Drawing on complexity theory, we investigate the structuring processes and underlying mechanisms underpinning the emergence of a new technology. Empirically, we track the emergence of blockchain technology by examining international patents issued between 2009 and 2020. Our results indicate that technology emergence follows an evolutionary trajectory that progresses from disordered to structured interactions among the technological elements, culminating in the formation of a technological core that acts as a pole of attraction for further interactions and delineates boundaries within the technological domain. Technology structuring is fueled by what we term ‘technology fitness’ and ‘self-reinforcing’ mechanisms that progressively transform primitive structures into more complex self-organized configurations. Our study offers a novel framework of technology emergence, highlighting how dispersed bits of technological knowledge gradually aggregate into complex structures that define the specific trajectory of a particular domain.

Keywords: technology emergence, blockchain, complexity theory, structuring, innovation, patents

"I hold it impossible to know the parts without knowing the whole, or to know the whole without knowing the parts in detail."

Blaise Pascal, 1669

INTRODUCTION

Emerging technologies are a critical driver of firm success and economic and social progress (Kapoor & Klueter, 2020; Soete & Freeman, 2012; Yoruk, Radosevic, & Fischer, 2023). New technologies emerge as a result of inventive processes during which technological elements — building blocks of an invention characterized by unique features (Fleming & Sorenson, 2004; Wang, Rodan, Fruin, & Xu, 2014) — are combined to solve a specific problem, laying the ground for technological advances (Dosi, 1982; Fleming, 2001; Park, Leahey, & Funk, 2023; Xiao, Makhija, & Karim, 2022; Yayavaram & Ahuja, 2008). This process of turning inventions into available knowledge is at the core of technological innovation (Savage, Li, Turner, Hatfield, & Cardinal, 2020; Somaya, Teece, & Wakeman, 2011; Teece, 2018).

Extant literature has primarily examined how inventors and organizations shape the modalities and trajectories through which new technologies emerge. Scholars who study modalities have focused on how existing technologies yield new ones. From this perspective, new technologies emerge from a synthesis of existing knowledge, which may produce variations under certain conditions, leading to new morphologies and even to new species of technology (Adner & Levinthal, 2002; Cattani, 2006; Fleming & Sorenson, 2001; 2004; Kodama, 1992; Levinthal, 1998; Schillebeeckx, Lin, George, & Alnuaimi, 2021). The research that has focused on trajectories, on the other hand, has mapped the evolutionary processes by which new technologies come into existence and change over time. Technology emergence is typically portrayed in terms of either path-dependent processes in which the initial technological choices become progressively more difficult to reverse (Arthur, 1989; Marin, Stubrin, & Van Zwanenberg, 2023; Sydow, Schreyögg, & Koch, 2009; 2020) or punctuated equilibrium, according to which relatively long periods of technological stability are punctuated by short bursts of fundamental change and discontinuity (Abernathy & Utterback, 1978; Anderson & Tushman, 1990; Grodal, Krabbe, & Chang-Zunino, 2023; Suarez, 2004).

Both perspectives presuppose that inventors and organizations play an important role in driving technology emergence. The modalities approach highlights the agentic micro-processes by which inventors and organizations manipulate pieces of existing knowledge to create new technologies. Conversely, the trajectories approach recognizes the role of inventors but argues that their agency is constrained by path-dependent trajectories that emerge over time because of technological lock-in. Although the two streams of literature have been very useful for promoting an understanding of technology emergence, less attention has been paid to the structuring process by which the micro permutations that underpin technological modalities crystallize into stable structures and macro trajectories. This limits our understanding of technology emergence as a dynamic process that unfolds across different levels of interaction. A more comprehensive picture of technology emergence should simultaneously consider the interaction between technological elements at a micro level, the underlying modalities, and the lock-in effects generated by technological trajectories at a macro level.

The purpose of this paper is to investigate how the structuring process that arises from interactions among technological elements affects the emergence of a new technology over time. We draw on complexity theory (Dick, Faems, & Harley, 2017; Nicolis & Prigogine, 1977; Prigogine, 1980; Prigogine & Stengers, 1984) to study technology emergence as a self-organizing process in which novel and coherent structures arise out of the interactions among smaller parts of the system (Goldstein, 1999). Two aspects of the theory are relevant to our objective. First, the complex systems theory recognizes that both emergent and intentional processes coexist and coevolve (Borzillo & Kaminska-Labbe, 2011). This is because the elements of complex systems have a semi-autonomous agency that allows them to adapt to their environment without centralized coordination. In this way, interactions among technological elements lead to the formation of organized patterns from the bottom up. Second, complex systems evolve by converting loose technological elements into consolidated technological cores. Because there is no centralized control, technological structuring is achieved through a process of self-organization in which interactions among elements spontaneously give rise to increasingly stable patterns (Morel & Ramanujam, 1999).

From an empirical standpoint, we consider the recently emerged blockchain domain — a set of technological elements characterized by a shared identity — as our focus of analysis, and track the emergence of international blockchain patents published between 2009 and 2020. We use network-based mapping to depict the growing complexity of blockchain technology over time and apply the knowledge decomposability measure to assess its structuration. Our results indicate that technology emergence is guided by technological fitness and self-reinforcing mechanisms. The technology fitness mechanism connotes the intrinsic quality of a specific technological element to connect with different technological elements within a specific technological domain (e.g., Fleming, 2001; Fleming & Sorensen, 2001; 2004). The self-reinforcing mechanism is based on a historical pattern of past connections according to which technological elements with numerous existing connections are more likely to acquire new ones, regardless of their intrinsic qualities (Gould, 2002; Sydow & Schreyögg, 2013). The interplay of these mechanisms generates increasingly structured interactions among technological elements, culminating in the formation of a technological core that acts as a pole of attraction for further interactions and delineates boundaries within blockchain technology. We then extend our analysis beyond the blockchain domain and conduct simulations to understand the potential outcomes of structuring processes when both technology fitness and self-reinforcing mechanisms are present or when only one of them is.

This study has significant implications for the technology innovation literature. First, by combining insights from studies on modalities and trajectories, we consider both the micro and macro dimensions of technology emergence to theorize the structuring processes through which technology emergence is accomplished. Second, we show how the dynamics underlying technology emergence combine in ways that go beyond the agentic intentionality of any one actor in the system, revealing how the semi-autonomous interactions of technological elements, through technology fitness and self-reinforcing mechanisms, facilitate technological structuring. Third, our study offers a novel understanding of the spatial and temporal dynamics that underpin processes of technology emergence.

This article is organized as follows. First, we review the literature on technology emergence and highlight the modalities and trajectory perspectives. Next, we draw on complexity theory to propose a framework that shows how the interactions among technological elements allow a technological domain to structure and become more organized over time. We then describe the setting, data, and methodology applied in our study. After presenting our results, we discuss the theoretical and managerial implications of this work and note its limitations and some avenues for future research.

THEORETICAL BACKGROUND

The dynamics of technology emergence

Dosi (1982: 151-152) has defined technology as a set of pieces of knowledge, both directly ‘practical’ (related to concrete problems and devices) and ‘theoretical’ (practically applicable but not necessarily actually applied). The suggestion from this perspective is that the procedures underpinning the emergence of new technologies are broadly similar to those that characterize the construction of scientific knowledge. In line with this conceptualization, scholars working on modalities have examined processes of technological speciation and (re)combination (Cattani, 2006; Cattani & Mastrogiorgio, 2021; Khanna, 2022; Kok, Faems, & de Faria, 2019; Schillebeeckx et al., 2021). Speciation has its roots in biology and refers to "the separation of one evolving population from its antecedent population, which in turn allows populations to follow different evolutionary paths" (Adner & Levinthal, 2002: 51). By analogy, new technologies come into being as a result of existing technological knowledge being transplanted to a new application domain, where it evolves in new directions (Adner & Levinthal, 2002). For example, Cattani (2006) has documented how Corning's knowledge and experience in the production of glass fibers for medical and military applications enabled it to identify opportunities in the seemingly unrelated domain of electronics. Likewise, Moehrle and Caferoglu (2019) observed several instances of technological speciation in the domain of camera technology, including the action camera, the depth camera, and the dashboard camera.

The modality of combination conceptualizes inventors who are embedded in organizations as agents of inventive processes over technological landscapes (Fleming & Sorensen, 2001, 2004; Grigoriou & Rothaermel, 2014; Schillebeeckx et al., 2021; Wang, 2024; Xiao et al., 2022). This inventive activity operates through a combination of existing and new technological components from previously joint or disjoint technology areas (Basalla, 1988; Hargadon, 2003; Hargadon & Sutton, 1997; Henderson & Clark, 1990; Kodama, 1992; Schillebeeckx et al., 2021). For example, Teece (1986) has illustrated how computed axial tomography (CAT) scanning technology resulted from cross-fertilization between computer technology and X-ray technology. According to Fleming and Sorenson (2001), a core element of technological evolution and other complex systems is the existence of an agent of recombination. For example, inventors combine new and old pieces of technological knowledge to produce new technologies based on fitness criteria, conveying a view of the technology as a spectrum of opportunities (Basalla, 1988; Fleming, 2001; Fleming & Sorenson, 2001).

Scholars who study technological trajectories have noted how inventors and organizations collectively shape patterns of continuity and discontinuity in technological emergence (Dosi, 1982). Specifically, continuity has primarily been framed in terms of path dependence (Arthur, 1989; 1994; David, 1985, 1986), a situation in which the cumulative effects of prior technological choices increasingly constrain the agency of inventors and only allow subsequent technological recombination to develop within the trajectory defined by earlier ones (Grodal et al., 2015; Grodal et al., 2023; Sahal, 1985; Sydow et al., 2009). Path dependence is triggered by a critical event — such as an inventor's decision, choice, or solution — that unintentionally sets the path-building process in motion. The technological path takes shape through self-reinforcing feedback mechanisms that support the initial event, generating a specific pattern that gradually becomes dominant and reduces the initial set of alternatives (Grodal et al., 2015). The consolidation of a dominant pattern may lead to a lock-in (Marin et al., 2023; Sydow & Schreyögg, 2013; Sydow et al., 2020) or even take on a deterministic character that results in alternative courses of action ceasing to exist (Clark, 1985; David, 1985).

While path dependence defines typical trajectories of technological progress, some scholars studying technology emergence through discontinuous trajectories have portrayed this progress in terms of punctuated equilibrium (Abernathy & Utterback, 1978; Anderson & Tushman, 1990; Tushman & Anderson, 1986; Tushman & Romanelli, 1985), a process in which periods of small, incremental change are punctuated by quantum leaps. Specifically, the emergence of a technological breakthrough may initiate a period of sharp divergence triggered by the existence of a plethora of technical variations (Anderson & Tushman, 1990; Utterback & Abernathy, 1975). Once a dominant design has emerged, the dynamics of technology competition prompt firms to select the technologies that are most likely to succeed and abandon the rest (Anderson & Tushman, 1990; Grodal et al., 2015; Utterback & Abernathy, 1975). Periods of technological progress can also be punctuated by moments of setbacks (Adner & Kapoor, 2016; Bakker, 2010; Kapoor & Klueter, 2020) that pose a technological challenge on the road toward technological advancement and may reverse the initial momentum.

When taken together, these studies portray technology emergence as a process that entails combining, separating, and recombining pieces of technological knowledge to form more consolidated entities. This is achieved by applying a different emphasis, however. Modalities highlight the micro processes by which inventors manipulate and synthesize pieces of technological knowledge, while trajectories highlight the emergence of macro structures that progressively diminish the agency of inventors until a situation of lock-in is reached. What is more, emergence is not accidental: it follows specific mechanisms that shape the configuration of a domain. In this regard, the research on modalities emphasizes the significance of integrating existing technological elements based on their mutual fitness to create a novel invention. Conversely, the studies on trajectories highlight how self-reinforcing interactions among technological elements contribute to the crystallization of a particular pattern over time.

Importantly, while inventors and organizations may drive the combination of technological elements at a micro level, they cannot fully control the outcomes of these combinations: that is, the macro structures that emerge at a macro level. There are two reasons for this. First, the success of technological combinations depends not only on the inventor’s abilities but also on the underlying characteristics of the combined elements and their interdependence. These interdependencies empower technology with an intrinsic autonomy that goes beyond the purposive behavior of inventors and organizations. Second, the relative influence of an individual inventor’s agency decreases over time as the technology gradually takes on a structure. In other words, as a technology crystallizes, part of the initial agency of its inventors is transferred to the technology itself, which acquires a life of its own (Latour, 1987).

If the dynamics of technology emergence involve structuring processes that comprise both micro and macro levels of interaction, then there is a need to better understand how these levels are connected throughout the emergence process. To bridge this gap, we draw on complexity theory (Dick et al., 2017; Goldenfeld & Kadanoff, 1999; Goldstein, 1999; Prigogine & Stengers, 1984; Tsoukas, 2017). Complexity theory complements current understandings by offering a view of technology emergence as the self-organized outcome of dynamic patterns that arise from the interactions among technological elements and progressively strengthen in scope and orders of complexity (Morel & Ramanujam, 1999; Thietart, 2016). Self-organization means that patterns and regularity emerge spontaneously in a system as a result of interactions among interdependent parts. It also implies that the interactions among the system's constituents are not centrally controlled, but rather that the interacting units combine locally to produce complex coordinated patterns of collective behaviors that change and adapt.

From this perspective, technologies come into being as a result of both the intentional agency of inventors and organizations and the emergent processes stemming from technological interdependencies. For example, the inventive act of writing an academic article is shaped by the author's intentions. Once the article has been published, however, it is appropriated by other members of the community, who might have different intentions and cite the paper for their own purposes. As Greenwood and Meyer (2008) point out, an idea that emerges from a paper is detached from its authors, who give up the exclusive right to interpret it. Ideas not only become semi-autonomous and take on a life of their own; they may also be path-dependent as the initial reception affects and narrows the core topic, which will later be explored further (Gould, 2002; Greenwood & Meyer, 2008). In a similar vein, a new technology relies on the input of its inventors, who manipulate technological elements to generate inventions, but once the invention has been granted a patent, it is appropriated by other inventors and organizations who use it for their own purposes. In other words, the agency of the inventor is to some extent 'delegated' to the patent (Latour, 1987), thus blurring the boundary between the agency of the inventor and that of the patent[1]. As the patent takes on a life of its own and becomes semi-autonomous, the influence of the individual inventor's agency decreases. Patented inventions therefore become particularly helpful for a study of the process of technology emergence.

The example also conveys a process of technology structuring, thus reinforcing the parallel between the emergence of new technologies and the construction of scientific knowledge (Dosi, 1982; Park et al., 2023). Just like inventors, academics are engaged in the production of novelty. Scientific innovation proceeds by means of an aggregation and accumulation of pieces of knowledge that take the form of an academic article. Scientific articles are ensembles of ideas, and when authors cite an article, they embrace one or more study's ideas, thus attaching new pieces of knowledge to the existing ones. In turn, subsequent authors further build upon these ideas which they have drawn to expand on what is known. And so the process continues. References to previous work are made based on suitability: authors chose to work on those ideas that fit for the purposes of developing their own contribution. Repeated references to the same idea or set of ideas included in articles reinforce certain claims, thus generating a conceptual core and crystallizing ideas into a coherent body of literature. The structuring of emergent technologies follows the logic of reinforced ideas

---

[1] The concept of delegated agency resonates with the literature on memetic evolution (Blackmore, 2000) according to which technological elements act as 'meme machines': that is, as replicators that fuel the evolution of ideas by means of memetic processes of copying, varying, and selecting knowledge irrespective of the intentionality of the initiators of those ideas.

over time. It proceeds through the accumulation of patents that are created by inventors, taken up by other inventors based on fitness, and progressively aggregated around technological cores that attract new patents within an emerging knowledge structure. To investigate these mechanisms at work, we will now present a model of technology emergence as a structuring process based on complexity theory.

Technology emergence as a structuring process

Complexity theorists conceptualize 'emergence' as the manifestation of novel, coherent structures capable of generating explicit patterns in complex systems (Dick et al., 2017; Goldenfeld & Kadanoff, 1999; Goldstein, 1999; Tsoukas, 2017). Complex systems consist of numerous interconnected elements that work together without any centralized control, functioning collectively as a whole (Prigogine & Stengers, 1984). When technological elements have extensive opportunities to interact, the system seems disorganized, and patterns are difficult to detect. However, spontaneous changes arising out of interacting elements can generate new configurations through self-organization (Nicolis, 1979; Prigogine & Stengers, 1984). Self-organization occurs spontaneously through the mutual adaptation of system elements (MacIntosh & MacLean, 1999; Miller, 1982; Thietart, 2016) as a result of which the micro interactions among the parts generate patterns of an increasingly higher order (Devezas & Corredine, 2002; Goldstein, 1999; Prigogine & Stengers, 1984). This implies that systems are characterized by ongoing interactions among multiple elements that continuously affect and shape the configuration of the system over time (Wang et al., 2014; Yayavaram & Ahuja, 2008).

Overall, complexity theory provides an understanding of technology emergence that brings together insights from both the modality and trajectory perspectives. On the one hand, it considers how efforts to combine interdependent technological elements generate connections and define technological modalities (Fleming & Sorenson, 2001), while on the other, it illustrates the self-organization dynamics by which micro interactions among technological elements crystallize into ordered patterns that define technological trajectories over time.

Our work develops these concepts within the framework shown in Figure 1. In this illustration, a complex system evolves through the aggregation of technological elements into patterns that progressively become more interconnected and complex, eventually culminating in the emergence of a new technology.

Insert Figure 1 about here

Figure 1(a) illustrates a situation in which technological elements are present but not yet connected. Although they are not linked in a formal sense, however, they may engage in initial efforts to form connections according to their potential interdependencies (Haken, 1981). These preliminary attempts can be viewed as ongoing experimentation through trial and error (Wang et al., 2014). The more of these attempts there are, the more likely it is that a connection among previously uncombined technological elements will be made. For instance, Branly's invention of the coherer in 1890 was key to the development of radio transmission; in 1894 Lodge tried to use it as a receiver, but the signals were not comprehensible. In the same year, Marconi experimented with wireless telegraphy, making several attempts not only with Branly's coherer but also with other technological components. Experimentation enhances the understanding of technological interdependencies and eventually leads to successful connections.

Figure 1(b) illustrates the earliest connections among technological elements, meaning that the first invention has given birth to the domain. Inventions are meant to solve specific problems (Dosi, 1982). These technical solutions may include two or more technological elements sharing certain technical features that facilitate their connection (Carnabuci & Bruggeman, 2009; Carnabuci & Operti, 2013). For instance, Marconi combined several technological components, such as Hertz's spark, Branly's coherer, Popov's antenna, Lodge's tuning circuit, and Morse code, to build the first long-distance wireless telegraph. All these components already existed (Figure 1a), but it was only after years of experimentation that Marconi was able to discover the interdependencies among them and connect them successfully. During this inception phase, all the technological elements exhibit the same level of fitness in the nascent technological domain and play a part in its emergence. Inventors shape the domain by selecting and connecting certain technological elements based on the specific goal of the inventing process (Capaldo, Lavie, & Messeni Petruzzelli, 2017; Grigoriou & Rothaermel, 2014; Schillebeeckx et al., 2021; Wang & Chen, 2018).

Figure 1(c) depicts how connections aggregate and generate elementary structures with the potential to subsequently evolve. Early inventions foster subsequent inventive activity that exploits previous combinations while attracting new technological elements. Although the technological interdependencies are the same as in Figure 1(b), some of the technological elements in Figure 1(c) exhibit a higher level of technology fitness, which is an intrinsic quality of a specific technological element to be connected, thanks to the inventors, who act as agents — with different technological elements within a specific technological domain. This mechanism explains why some technological elements are more attractive than others (for example, technological element C_1) even though they possess the same number of connections. By using their knowledge and creativity, inventors can activate the technology fitness mechanism when they embody technical knowledge that is malleable and can easily connect with other technological elements, thus increasing a system's complexity. The modalities approach is helpful here as a means of explaining the mechanism of technology fitness because the original attributes and intrinsic characteristics of the technological elements serve as drivers for recombination (Fleming, 2001; Kok et al., 2019; Wang et al., 2014). For example, in the early 1800s, the British chemist Humphry Davy discovered a chemical reaction that generated hydrogen. His discovery attracted further connections and was applied to the automotive industry in 1807 when the Swiss inventor Francois Isaac de Rivaz created a four-wheel vehicle powered by hydrogen and oxygen. In our framework (see Figure 1c), hydrogen can be represented by the technological element C_1. Thanks to its fitness, it allows connections with many other elements, thus increasing the system's complexity. These examples show how inventors are relatively free to create something from scratch by combining different technological elements (Figure 1b). Their agency diminishes compared to Figure 1(b), however, since they are more likely to combine technological elements that exhibit a high degree of technology fitness (i.e., C_1) while also being free to discover new connections.

Figure 1(d) captures the self-reinforcing mechanism by which specific technological elements become predominant over time. For instance, de Rivaz's hydrogen-powered vehicle received positive feedback that was confirmed in the late 1930s, when William R. Grove created a hydrogen fuel cell. Both de Rivaz's and Grove's intuitions were further reinforced by a Belgian inventor who developed and tested a large vehicle with a combustion engine in the 1860s. In the move from one invention to another, some technological elements (including electrodes and electrolytes) were ignored and disappeared, while others, such as the cylinder, ignition systems, piston, crankshaft, and fuel storage, became prerequisites for further developments. This means that subsequent efforts by inventors became constrained by these core elements. For the sake of clarity, in Figure 1(d), the self-reinforcing mechanism can be observed in the technological elements C_1 and C_2 (see Figure 1(d), which gradually gain prominence and form a more stable structure compared to Figure 1(c). Subsequent inventions relating to the combustion engine reinforced the link among these technological elements. These examples show how an initial path becomes increasingly crystallized with the potential to set a dependent trajectory. The predominance of specific paths constrains the agency of inventors since they have less influence when it comes to changing or modifying those paths once they have been established.

Moreover, the emergence of a more complex structure around two technological elements (C_1 and C_2 in Figure 1d) generates a pole of attraction. Subsequent inventions are built around core technological elements that are further reinforced by increasing the number of existing connections, but inventors also introduce new technological elements, thus expanding the scope of the technology. The fundamental difference between technology fitness and self-reinforcing mechanisms lies in the criteria by which technological elements acquire new connections. The technology fitness mechanism is based on the intrinsic quality of a particular technological element to connect with other technological elements within a specific technological domain. Technology fitness makes some technological elements more attractive for new connections, regardless of their previous number of connections. In contrast, the self-reinforcing mechanism is predicated on a historical pattern of past connections where technological elements with many existing connections are more likely to gain new ones irrespective of their intrinsic qualities. This implies that the technology fitness and self-reinforcing mechanisms can work jointly. For example, the anode is a core component of hydrogen fuel cell technology. It is essential for hydrogen oxidation and was initially characterized by a high level of technology fitness thanks to its compatibility with a variety of catalysts. This intrinsic quality attracted extensive research and development that led to a series of inventions. As these components became more established in the technological domain, self-reinforcing mechanisms started to influence their further development. The widespread use and proven performance of the anode encouraged further research and optimization, thus reinforcing its technological dominance. The activation of the two mechanisms depicted in Figure 1 (d) allows a technology to emerge.

Overall, our model explains technology emergence through two core mechanisms — technology fitness and self-reinforcing — that shape the configuration of a new technology. First, the technology fitness mechanism is activated by inventors as a result of the intrinsic quality of a specific technological element to connect with other technological elements within a specific technological domain. In line with the modalities approach, these connections are guided by both the intrinsic attractiveness of the technological elements and the inventors' ability to embody them in an invention (Dosi, 1982). Technological elements with high levels of technology fitness act as a sort of magnet, attracting heterogeneous but compatible technological elements and fostering the integration of these elements by steering them in a specific direction. Second, the self-reinforcing mechanism crystallizes this direction by bonding connections in technology structures. The concurrent activation and persistence of these two forces transform elementary and easily malleable structures into more complex and rigid ones. The increased structuring restricts subsequent technology development. As a result, technological elements become less dependent on the inventor's agency and contribute to further structuring through their semi-autonomous agency. Indeed, in this case, a single inventor cannot intentionally force the positioning of a technological element within the technological domain, for instance by moving one element from a peripheral to a more central position.

METHODOLOGY

Following the theoretical framework outlined above, this research examines technology emergence as a structuring process in which sets of technological elements connect on an ongoing basis and generate spontaneous structure through the activation of technology fitness and self-reinforcing mechanisms. To investigate the dynamics underpinning technology emergence and how they shape the configuration of a technology, we examine the recently emerged blockchain technology and track how it acquired structure over time.

We proceed as follows. First, we use network analysis to map and visualize connections among technological elements and detect the two mechanisms at work as blockchain technology emerges (Wang et al., 2014; Yayavaram & Ahuja, 2008). Second, we apply the decomposability measure (Yayavaram & Ahuja, 2008) to assess the structuring of the technological domain and show the interaction of the technology fitness and self-reinforcing mechanisms. Last, we use simulation techniques (Oberg, Korff, & Powell, 2017; Pham, Sheridan, & Shimodaira 2016; 2020) to show how the two mechanisms shape the structuring and (non-) emergence of any technology. We develop a simulation to create controlled environments within which we can vary parameters representing our proposed mechanisms and observe the resulting dynamics. This allows us to consider the roles of these mechanisms in shaping technological domains beyond what we observe in the context of our study of the emergence of a specific technology.

Setting

Blockchain is an emerging software-based technology that has become essential for firms' success and survival in the digital era (Bailey, Faraj, Hinds, Leonardi, & von Krogh, 2022; Chen, Pereira, & Patel, 2021; Hsieh & Vergne, 2023; Iansiti & Lakhani, 2017; Tapscott & Tapscott, 2017). Developed by Satoshi Nakamoto in 2008, it is one of the megatrends that are shaping today's businesses and society (World Economic Forum Report, 2020). Nakamoto's (2008) white paper proposed the virtual currency known as Bitcoin to facilitate transactions. The author conceived blockchain as a distributed data ledger that would be capable of safely storing digital transactions without the intervention of a central authority, thus revolutionizing the traditional concept of currency. The emphasis on a peer-to-peer network generates currency exchanges between users by recording all transactions in a shared ledger that is dispersed across the world (Kher, Terjesen, & Liu, 2020). The first Bitcoins were created in a collaborative open-source environment by Nakamoto, who was active until mid-2010. The project was subsequently transferred to the community.

Although it was initially aimed at the financial sector, blockchain's scope has extended to the realm of cryptocurrency, enabling a wide range of applications of blockchain technology in the domains of gaming and entertainment, mobility, supply chains, and healthcare, among others (Biais, Capponi, Cong, Gaur, & Giesecke, 2023; Chen et al., 2021; Clarke, Jürgens, & Herrero-Solana, 2020; Schmeiss, Hoelzle, & Tech, 2019). In this regard, a prominent role has been played by Vitalik Buterin, who in 2014 introduced Ethereum[2], a next-generation blockchain platform designed for executing smart contracts (a self-executing contract with the terms of the agreement between the parties directly written into lines of code). Because of its vast potential, numerous firms working on blockchain technology have emerged, pushing them to protect it from further development. This need for protection has translated into a rush to patent blockchain inventions (Clarke et al., 2020; Kaye & Wagstaff, 2017). An analysis of these patented inventions can therefore provide a comprehensive picture of the structuring process of the blockchain domain over time.

Data collection

We collected international blockchain patents that are globally protected through the World Intellectual Property Organization to reduce any bias in national or regional patent activity (Criscuolo & Verspagen, 2008). We retrieved the patent documents using the Derwent Innovation Database[3], which enables the grouping of patents into families to reduce redundancy in a sample (Harrigan, Di Guardo, Marku, Velez, 2017). To this end, we used

[2] https://ethereum.org/669c9e2e2027310b6b3cdce6e1c52962/Ethereum_Whitepaper_-_Buterin_2014.pdf

[3] Derwent Innovation Database is one of the most comprehensive worldwide patent databases. It includes information on around 70 million patents issued by 52 patent authorities worldwide.

Clarivate Analytics, whose experts developed the search queries in Table 1. Searches were run on the patent title, claims, or abstract. The combination of the three queries after any duplications had been removed led to a final sample of 1,388 patent families distributed in a timeframe from 2009 to the 2nd trimester of 2020.

Insert Table 1 about here

We used the Derwent World Patent Index (DWPI) as our patent classification system. We reviewed the DWPI patent classification codes in depth to determine whether any of the codes had been reclassified, as this might have introduced bias into our data. We found that there had been no patent reclassification during the period under examination. Next, we transformed our sample into an appropriate data structure by pooling patents according to the year they were applied for.

Mapping and visualizing connections and mechanisms

This study adopts a network-based approach, employing patent co-classification as a particularly suitable method for revealing the structure and the earliest dynamics of a technological domain, thereby facilitating the design of maps without the time-lag associated with citation-based methods (Engelsman & van Raan, 1994; Tijssen, 1992). To conduct our network analysis, we first calculated co-occurrence matrices to capture yearly changes in the frequency of the appearance of two technological elements in patents. P denotes the set of all patents. Each patent $p \in P$ is characterized by an application year $y(p)$ and an associated set of technological elements $T(p)$ identified by the patent classification codes. For each separate year y observed in our dataset we defined an N x N matrix A_y where N represents the total number of unique technological elements identified across all patents. The entry A_{ij}^{y} in the matrix A_y

quantifies the connections between technological element i and technological element j for application year y. Each entry in the matrix is defined as:

$$A_{ij}^{y} = \sum_{p:y(p)=y} \mathbb{I}(i \in T(p) \wedge j \in T(p)) \quad (1)$$

where $\mathbb{I}$ is the indicator function that takes a condition as its argument and returns 1 if the condition is true or 0 otherwise. In our case, the indicator function checks if both technological elements i and j are present in the set $T(p)$ of a given patent p. If both are present, it returns 1; if they are not, it returns 0. The summation then counts the number of patents in year y where both i and j co-occur.

Using the matrices A_{ij}^{y}, we then proceeded to aggregate these matrices over specific time windows to capture cumulative interactions. Once disclosed, the technological knowledge included in patents becomes part of the collective technological landscape and can affect subsequent inventions. Therefore, for a series of end years Y = {2010, 2012, 2015, 2020}, we built cumulative matrices C_Y such that: C_Y = $\Sigma_{y-2009}^{Y} A_y$. Each matrix C_y includes the cumulative co-occurrence of technological elements from the base year 2009 up to the respective end year in Y.

Using a multivariate analysis, we transformed the high-dimensional data in C_Y into a reduced-dimensional space. For network analysis, we interpreted each cumulative matrix C_Y as a weighted undirected graph G_Y. The technological elements in G_Y correspond to the unique technological elements (that is, the patent classification codes), with connection weights determined by the aggregated co-occurrence frequencies from the matrix (Yayavaram & Ahuja, 2008). The size of the technological elements reflects the frequency with which a particular technological element appears in a pool of patents: the greater the frequency, the larger the size. The more two classification codes co-occur in patent documents, the more intense their interaction will be. According to our theoretical framework, the initial phase of technology emergence is characterized by the presence of a small number of technological elements with limited interconnections, reflecting the initial outcome of the inventive processes. As these processes advance, technology fitness allows for the integration of new technological elements. This leads to a scenario of increased complexity translated into a high number of technological elements. Some of these technological elements become more prominent, activating a self-reinforcing mechanism that further increases their dominance in the technology domain.

Measuring technology structuring

We used the decomposability measure to capture the structuring process resulting from the interplay of technology fitness and self-reinforcing mechanisms. This measure quantifies both the cohesiveness of a structure and the strengthening of connections over time (Simon, 1962; Yayavaram & Ahuja, 2008). Specifically, the technology fitness mechanism increases the number of new connections, thus adding complexity, while the self-reinforcing mechanism enhances the number of strong connections associated with specific elements and aids in forming a core within the technological structure. To assess how technology is structured, we first identified each technological element's microstructure, which includes all the direct connections of the focal technological element with its neighbors, as well as the connections between these neighbors (Yayavaram & Ahuja, 2008). We then categorized connection patterns as strong or weak according to the frequency of connections between two technological elements relative to all possible connections inside the focal technological element's microstructure. Following prior literature, we proceed in determining a threshold connection value cv_i operationalized as:

$$cv_i = \frac{\sum_{j=1}^{r} w_j}{c_i} \qquad (2)$$

where w_j represents the number of connections occurring between technological elements n_i and n_j. We indicate with r the number of technological elements in the microstructure. C_i is the number of all possible connections of the focal technological element n_i in the microstructure[4]. cv_i is thus a positive discrete number for each technological element n_i If the observed number of co-occurrences is above the threshold connection value, the connection pattern is strong. Conversely, values below the threshold indicate weak connection patterns. Then, we proceed with assessing the integration level I_{ni} defined for each focal technological element n_i as $I_{ni} = \frac{q}{C_i}$, where q refers to the number of weak connection patterns.

Finally, decomposability measure D is determined as:

$$D = 1 - \sum_{i=1}^{N} (z_i \text{ x } I_i) \tag{3}$$

where z_i ranges between 0 and 1 and represents the relative size of each technological element (that is, the ratio of the number of occurrences of a technological patent class and the total number of occurrences), I_i assumes values between 0 and 1 and measures its integration value, and N is the number of total technological elements. This formulation aggregates the technological element data, combining aspects of size and integration to measure how cohesive the overall structure is.

The decomposability measure, which ranges from 0 to 1, helps us understand the structuration process. Values between 0 and 0.5 reasonably indicate a non-decomposable structure. In this scenario, technological elements are interconnected, but the connections are distributed so broadly that no distinct structure or pattern emerges. For values greater than 0.5 but less than 1, the structure is considered to be nearly decomposable. Here, the structure is

[4] C_i accounts for all possible connections of the focal technological element n_i within the microstructure, including both the direct connections of the focal technological element with its neighbors and the connections among these neighbors (Yayavaram & Ahuja, 2008).

more discernible, with a core technology emerging amidst weaker connections. Finally, values equal to 1 signify a fully-decomposable structure. This represents a scenario in which the technology is characterized by a lack of weak connections, meaning that the technology is highly self-contained, with each part operating independently rather than interdependently. As a result, the technology becomes locked in, with each component functioning in isolation, leading to a system that is resistant to external influences or integration with other technologies. This condition reflects a rigid structure that limits the potential for evolution. Following our theoretical framework, we expect a nearly decomposable structure (values higher than 0.5 and lower than 1) in the blockchain context, with increasing values of the decomposability measure over time. This is the result of the technology fitness mechanism, which produces an increase in weak connections, and the self-reinforcing mechanism, which fosters the emergence of a technology core. We have included an additional example in Appendix A with more detailed operationalization.

Estimating technology fitness and self-reinforcing mechanisms

According to our theoretical model, technology emerges thanks to technology fitness and self-reinforcing mechanisms. To jointly estimate these mechanisms, we use the PAFit method. This method is particularly suitable to model networks where both the number of connections between technological elements and their individual characteristics evolve dynamically (Pham et al. 2016). Following Pham et al. (2020), we indicate $P_i(t)$ as the probability that a technological element n_i receives a new connection at time t:

$$P_i(t) \propto \eta_{i.} \text{ x } A_{ki}(t) \tag{1}$$

where η_i is the technology fitness of technological element n_i, A_k denotes the self-reinforcing mechanism, and $k_i(t)$ is the number of connections technological element n_i has at time t.

When considering the technology fitness mechanism in isolation, the probability $P_i(t)$ that a technological element n_i connects at time t is given by a positive number $\eta_{i.,}$ independent of the number of connections the technological element possesses (k is not considered here). To measure η_i, in the formalization (1) the effect of the self-reinforcing mechanism is neutralized by setting $A_{ki}(t) = 1$ (Pham et al., 2020; Caldarelli, Capocci, De Los Rios, & Muñoz, 2002). The values of η_i are typically higher than 0, since the absence of technology fitness η_i =0 would imply the technological element cannot form a new connection. Differences between technological elements in terms of values η_i explain why technological elements that joined the technological domain later can surpass those that were already there.

When the self-reinforcing mechanism is considered in isolation, the probability $P_i(t)$ that a technological element n_i connects at time t depends on the existing number of connections $k_i(t)$ that specific technological element n_i already possesses; k ranges from 0 to the maximum number of connections composing the technology structure. The self-reinforcing mechanism A_k assumes a log-linear form $A_k = k^{\alpha}$, where α represents the self-reinforcing exponent (Pham et al., 2020; Krapivsky, Rodgers, & Redner, 2001). Understanding the value of the α exponent is fundamental because it explains to what extent established technological elements continue to dominate and thus influence technology structuring. When $\alpha = 1$ indicates a situation in which a few technological elements become very highly connected. Values of $\alpha < 1$ suggest that most technological elements have a moderate number of connections, however, there are very few highly connected. In contrast, when $\alpha > 1$ represents a lock-in scenario where highly connected core technological elements dominate the overall technological domain with less chance for less prominent technological elements to emerge.

Finally, we chose a 95% confidence interval to make our results more robust. The estimation process in PAFit utilizes a Majorization-Minimization (MM) algorithm, which in the context of our model, ensures efficient and effective estimation of both technology fitness and self-reinforcing mechanisms (Pham et al., 2016).

RESULTS

Structuring of the blockchain domain

Figure 2 provides a comprehensive overview of the structuring process observed within blockchain technology, illustrating the results of the two mechanisms at play. By delineating the technological elements and mapping their connections over time, the figure highlights technology emergence and evolution in terms of complexity and structuring. We explain this process using four distinct time windows to convey how the technological elements self-organize, attract each other, and self-reinforce their position. Each window in Figure 2 reports the number of patents, the number of technological elements, the number of connections, and the top 10 most connected technological elements ranked according to their total number of connections. The decomposability average measure is also included to capture the degree of structuring and assess temporal changes.

Insert Figure 2 about here

Moving from the upper-left-hand side, Figure 2 (I) illustrates blockchain's earliest connections in the 2009-2010 timeframe. The combination of 16 technological elements included in five patented inventions is an expression of the initial efforts of inventors at a micro level. These results are consistent with our theorization (as depicted in Figure 1b and further in Figure 1c). In particular, the mechanism of technology fitness is evident in this phase, and it may determine different paths for the technological elements. For instance, the technical features of T01-D01 (data encryption and decryption) allowed it to establish 16 successful connections (exhibiting higher technology fitness) while T01-F02 (interrupt, multi-programming, multi-tasking) was only able to connect once. Structuring can therefore be considered as the outcome of successful connections among technological elements that self-organize. The decomposability measure for this time interval is consistent with these observations, as it displays a value that falls into the nearly decomposable level (0.605).

Figure 2 (II) shows a more complex structure that transforms the blockchain domain into a new configuration consisting of 27 technological elements and 216 connections in the 2009-2012 timeframe. The key aspect that needs to be highlighted in this snapshot is the appearance of the self-reinforcing mechanism. This dynamic is illustrated by the initial predominance of one technological element — T01-J05 (data processing systems for administration, commerce, or information retrieval) — over the rest. Consistent with our model (see Figure 1d), the reinforced connections foster structuring, as evidenced by an increase in the decomposability value (0.809) for the time window. At the same time, it is also possible to observe the technology fitness mechanism at work. This mechanism explains why technological elements with the same number of connections evolve in different ways, as is the case with W01-A05 (secret communication), which was able to attract more connections than T01-J12 (program management), even though they had had the same number of connections in the previous time frame (10 each). The emergence of an initial, albeit fragile, path that was primarily related to Bitcoin reduced the scope of the experimentation — an early, but weak, signal of the diminishing agency of the inventors.

Figure 2 (III) depicts the cumulative growth of blockchain in the time frame 2009-2015. Compared with the previous time frames, the domain has acquired greater complexity (45 technological elements linked 746 times), and a higher degree of structuring has led to the generation of an initial technological core. In this timeframe, we see that the domain includes almost four times as many patents compared to the previous period (41 vs. 12) while the number of technological elements has less than doubled. This means that the inventors are increasingly keen to combine existing technological elements that fit together better. Figure 2 (III) shows how some technological elements increased their size and consolidated their connections (signaled by thicker connections). Indeed, all the technological elements included in the list of the highest connected technological elements (Figure 2) acquired new connections to varying degrees. These differences in amount depend on the magnitude of and interplay between technology fitness and self-reinforcing mechanisms. For instance, T01-N01 (internet and information transfer — applications) shifted from 8th position (9 connections) in the second timeframe to 1st position (84 connections) in the third. Thanks to the self-reinforcing mechanism, existing connections among technological elements were confirmed, while the technology fitness yielded new ones. This is not surprising, because the field began to proliferate during this time window thanks to Ethereum, whose white paper was released in 2014. Ethereum highlights the fundamental role played by its inventor, Vitalik Buterin, whose agentic action paved the way for the rapid development of technology beyond the financial sector. Domain structuring over the seven-year window is evidenced by the increase in the decomposability value (0.813), indicating a more cohesive structure over time.

In the final window (2009-2020) depicted in Figure 2 (IV), we observe the exponential growth of the blockchain domain in terms of the number of patents (1,388), number of technological elements (287), and number of connections (27,780). This intensive inventive activity has profoundly changed the domain configuration, which now reveals a clearer technological core. The four technological elements listed in Figure 2 (IV) have 45% of all the connections while representing 1% of the overall domain. This is an expression of the self-reinforcing mechanism, which has consolidated certain specific technological elements. Technology fitness has also fostered complexity by attracting new technological elements and shaping the blockchain domain. For example, technological solutions such as cryptography, proof of work, and proof of stake are considered to have greater fitness because they enhance the security of the blockchain. The accumulation of micro interactions among the technological elements has formed a specific trajectory that is now revealed at a macro level. The increase in structuring (2009-2020) is confirmed by an increase in the decomposability value (0.922), which depicts a nearly decomposable structure with defined microstructures and numerous connections that bridge them. Also, thanks to the interplay between the two mechanisms, the primitive core described in Figure 2 (III) is transformed into a technological core that serves as an “attractor”, encompassing a domain’s identity. A technology core can be difficult to change unless self-reinforcing and technology fitness mechanisms definitively cease.

It should be noted that almost all the technological elements listed in the top 10 most connected elements in the first timeframe (2009-2010) also appear in the top 10 lists in subsequent timeframes, although more than a decade has passed. The massive contribution of numerous inventors worldwide is heavily grounded on and profoundly influenced by the initial intuition of a few. We observed that path dependence increases with time while the inventors’ agency decreases as technology trajectories become more evident. Indeed, inventors face technology constraints that ‘force’ them to comply with a technology core and a defined, although malleable, technological structure. New technological elements that join the blockchain domain cannot occupy a random position; rather, they must self-organize according to their connection with the existing technological elements. To capture the post-Ethereum structuring process, we mapped the blockchain domain in the 2014-2020 time window. The results are very similar to those from 2009 to 2020, suggesting the importance of the role played by Ethereum in shaping the blockchain domain.

Technology emergence: joint estimation of the mechanisms at work

To show the joint influence of the two mechanisms on technology structuring, Table 2 includes the estimation of the α exponent when considering the self-reinforcing mechanism in isolation (Model 1) and the joint estimation of α when both self-reinforcing mechanism and technology fitness are considered (Model 2). Blockchain technology presents a sub-linear case in which α <1 in both models, with values of 0.923 and 0.907 for Model 1 and Model 2, respectively. This result confirms that while technological elements with more connections are more likely to acquire even more, the rate at which they receive new connections is not directly proportional to their current number of connections (k).

Moreover, when the technology fitness mechanism is included in Model 2, the α exponent decreases. This result is consistent with our theorization that both technology fitness and self-reinforcing mechanisms jointly affect technology structuring. Indeed, the self-reinforcing mechanism is not the sole driver of technology but also technology fitness is present. The latter allows technological elements with fewer connections to become more influential, independently of the number of existing connections, thus leading to a more heterogeneous technology structure. Note that the 95% confidence intervals do not include the value 1, making the results of a sub-linear case more robust. Although the details are beyond the scope of the present study, in Appendix B, we include additional analyses aimed at measuring the individual contribution of the two mechanisms in shaping blockchain technology.

Insert Table 2 about here

Simulating different paths of technology emergence

We carried out simulations to generalize from our observations in the blockchain domain and show how technology structuring unfolds when the two identified mechanisms operate independently or jointly. By simulating the two mechanisms at work, we were able to assess alternative configurations of technology (non-)emergence against the path observed for blockchain technology, thus providing a further test of the robustness of our results. The methods we used to develop these simulations are included in Appendix C. In this subsection, we present the results in terms of the different configurations that can potentially arise in any technological domain.

Figure 3 visualizes the simulation outcomes. Three scenarios are considered: 1) only the technology fitness mechanism is present; 2) only the self-reinforcing mechanism is present; and 3) the technology fitness and self-reinforcing mechanisms work jointly.

Insert Figure 3 about here

Simulation 1 presents a scenario in which the presence of technology fitness has fostered connections with new technological elements but the formation of the technological core is not evident. The absence of a self-reinforcing mechanism leads to a more distributed and interconnected structure, resulting in a non-emergence of the technology. The technology is in its earliest stages of development, during which a variety of paths can still be explored through experimentation. Without a clear core, however, this scenario involves a high degree of uncertainty regarding the evolution of technological patterns. This situation depicts a fully decomposable structure in which connections are broadly distributed and no specific trajectory is established. Considering that no constraint is imposed by a dominant trajectory, inventors are free to generate unexpected combinations of technological elements that might give rise to profound changes in the technology.

In Simulation 2, the technological structure is shaped exclusively by the self-reinforcing mechanism. As discussed in our theoretical framework, the technology fitness mechanism is essential because it enables connections. To simulate the absence of the technology fitness mechanism, all the technological elements are considered as having an equal ability to attract, and connections occur on a random basis. In this simulation, we observe the powerful force of this mechanism, which has fostered a dense, interconnected technological core at the expense of complexity and variety, and as clearly emerges, the number of elements composing the technology decreases significantly and a rigid trajectory is laid out. Under these circumstances, the technology becomes locked in around its core elements, thus limiting experimentation with new technological combinations and restricting growth opportunities. This scenario suggests a non-decomposable structure that almost lacks even weak connections. Core technological elements are profoundly interconnected, and changing even one can have significant implications for the entire structure. A scenario like this highlights the over-reliance of the technological domain on a few technological elements, offering inventors very limited options for technological advancement.

Finally, Simulation 3 depicts a general model of technology emergence in which the technology fitness and self-reinforcing mechanisms work together. Here, the structure appears to be nearly decomposable, with sets of strongly-connected technological elements forming a core, even though numerous weak connections are also present. Within this framework, inventors reinforce the recombination of core technological components, while exploring multiple new technological options. This scenario reflects the case of blockchain technology, where certain technological elements have activated the self-reinforcing mechanism, becoming dominant and crystallizing their position at the core. Technology fitness has attracted many technological elements, further fostering exploration. When both mechanisms are at work, even peripheral technological elements can potentially enter the core. This entry can be facilitated by an exponential growth of connections with one or more existing core technological elements. Thus, the model illustrates how the emergence of technology is the outcome of complex interactions between technology fitness and self-reinforcing mechanisms. These interactions not only allow emergence but also shape any technological domain.

DISCUSSION

The aim of our study was to investigate the structuring processes that underpin the emergence of a technology. We have drawn on complexity theory to build a theoretical model that depicts how sets of technological elements that have been synthesized in patented inventions self-organize and gradually aggregate into more complex structures that serve as a basis for further technology development. The progressive aggregation and structuring of the technological elements occur through the interaction of two distinct mechanisms: technology fitness and self-reinforcing. The technology fitness mechanism embodies the attractiveness force working at a technological element level, while the self-reinforcing mechanism synthesizes the force of a connection between technological elements, and the emergence of a predominant connection over time crystallizes patterns and trajectories, leading to technology emergence.

The application of the model to the blockchain domain showed that an increasing number of inventions and the modalities of putting together new and existing technological elements — facilitated by the technology fitness mechanism — considerably increased the complexity of the domain. The successful combination of technological elements reinforced specific connections, thanks to the self-reinforcing mechanism. Furthermore, the joint activation and persistence of both technology fitness and self-reinforcing mechanisms enabled certain technological elements to attract numerous others, strengthening their connections and thereby consolidating into a technology core. Our simulations extended the dynamics of technology emergence observed in the blockchain domain to other technological domains based on variations in the presence or absence of the technology fitness and self-reinforcing mechanisms. Our results suggest three theoretical contributions, which we discuss below.

Understanding technology emergence as a structuring process

Our study brings together two important dimensions of technology emergence. First, it bridges the micro and macro processes of technology structuring; and second, it combines the agency of inventors with that of technological elements. Existing studies on the modalities of emergence have focused on the micro dimension of technology speciation and recombination. From this perspective, emergence is conceptualized as an aggregation process that involves elementary pieces of knowledge combined in an invention (Basalla, 1988; Cattani, 2006; Cattani & Mastrogiorgio, 2021; Fleming & Sorenson, 2004; Hargadon, 2003; Kodama, 1992; Levinthal, 1997; Xiao et al., 2022). In contrast, the literature on trajectories has predominantly examined the macro dimension of technology emergence and development, disentangling patterns and directionalities (Anderson & Tushman, 1990; Tushman & Anderson, 1986; Utterback & Abernathy, 1975). Although these two perspectives represent the core foundations of innovation literature, they have been hitherto considered separately.

By integrating research on modalities and trajectories, our study suggests that technology emergence results from the interaction of micro and macro level dynamics that gradually take a system from simplicity to complexity and from loose interactions to structured patterns. Specifically, activating the technology fitness mechanism facilitates a broader combination of technological elements, thus increasing complexity, while activating the self-reinforcing mechanism generates patterns that crystallize into cores and progressively structure the system. These observations are theoretically important because they explain how a technological domain is shaped and under what conditions of emergence, non-emergence, and locked-in scenarios.

Our model of semi-autonomous agency also expands current understandings by recognizing both the efforts of inventors and the agentic properties of technological elements during processes of technology emergence. Admittedly, technological innovation is a human endeavor that relies on the initiative of multiple inventing subjects and the sharing of knowledge between academic scientists and industrial research managers (see, for example, Evans, 2010; Fleming & Sorenson, 2001): on the one hand, inventions imply the existence of an agent of recombination (Fleming & Sorenson, 2001; Kok et al.,2019), while on the other the institutionalization of inventions into patents with legal status turns human inventive acts into tangible technological elements that acquire semi-autonomous agency. In this regard, the emergence of a technology is similar to the construction of scientific knowledge (Dosi, 1982), in which initial ideas gradually detach from their originator, becoming semi-autonomous and taking on a life of their own (Gould, 2002; Greenwood & Meyer, 2008). While combinations of technologies are created by inventors or organizations, the success of those combinations also depends on the underlying characteristics of the technological elements themselves, and hence, we argue that a model of technology emergence should simultaneously consider the agentic actions of inventors and organizations and the self-organizing processes arising from the interacting technological elements.

Our study shows how the mechanisms of technology fitness and self-reinforcing affect inventors' efforts by shaping technology opportunities and constraining future developments. In the case of the blockchain domain, we observed that the inventor's initial intuition to combine key technological elements such as data encryption and decryption, secret communication, and data processing systems crystallized into a technology core. The path-dependent trajectory compelled subsequent inventors to follow the emergent pattern, and so the inventor's agency to independently shape technology gradually decreased. This happens because technological elements can self-organize through semi-autonomous agency, following rules of technology fitness and self-reinforcement. Although the self-reinforcing mechanism increases over time, the blockchain field does not exhibit a locked-in situation, which suggests that changes to and the persistence of these mechanisms may counteract the decrease in the inventors' agency. These findings are theoretically important because they contribute to debates on the agency of things (Latour, 1987) relating to processes of technological emergence. They suggest that inventors delegate agency to patents, which interact in a semi-autonomous manner and are eventually combined in non-predictable technological configurations. These agency mechanisms shape technological modalities and trajectories.

The role of space and technological distance

This study has implications for our understanding of the spatial dimension of technology in general, and specifically the role of technological distance in management studies (Capaldo et al., 2017; Rosenkopf & Almeida, 2003; Rosenkopf & Nerkar, 2001; Wang & Chen, 2018). Technological distance, which is commonly viewed as the difference in the technological profile of two patent portfolios (Nooteboom, Van Haverbeke, Duysters, Gilsing, & Van den Oord, 2007; Savage et al., 2020), has mostly been investigated in contexts like mergers, acquisitions, and inter-company collaborations to examine partner selection and innovation performance (see Ahuja & Katila, 2001; Mowery, Oxley, & Silverman, 1998). Studies in this stream of research have mainly assessed technological distance by taking patents and simply counting the number of classification codes shared by two enterprises' portfolios (Diestre & Rajagopalan, 2012). A more recent study by Capaldo et al. (2017) has investigated technological distance at a patent level by accounting for the distance of technological elements included in a single patent. While these patent-based indicators are effective for analyzing large datasets, their lack of inherent temporal and sectoral dynamics is a limitation.

Our results challenge previous understandings (see, for example, Ahuja & Katila, 2001; Capaldo et al., 2017; Rosenkopf & Nerkar, 2001), and highlight the fact that technological distance cannot be treated as an absolute measure but rather in the context of a specific technological domain. Technological elements have varying roles in the domain, which may change over time. We showed that in the case of blockchain technology, the structuring process brought together distant, previously unconnected technological elements, such as cryptography, secret communication, and financial applications. Once the newly-born domain has been formed and its technological core has been structured, a new trajectory is defined. For inventions to align with this emerging trajectory, they must incorporate components of blockchain technology. Thus, individual technological elements of subsequently patented inventions may seem distant when viewed separately but are closely linked when considered within the context of blockchain technology.

When viewed from this perspective, measures of technological distance should consider both the interactions that exist between technological elements in a given technological domain and the evolution of these interactions. Several key recommendations suggest themselves here. Firstly, patent-based measures of technological distance should preserve the granularity of technology knowledge embedded in inventions by looking at the multiple and distinct patent classification codes. Secondly, to account for the interaction between technological elements, the co-occurrence of patent classification codes should reflect temporal changes in their likelihood of appearing jointly within a specific domain, indicating whether or not they are positioned at the core of the technology. The introduction of a dynamic technological distance indicator may prove to be an important advance in this regard. Lastly, as these interactions change over time, the calculated likelihood should refer to a specific timeframe. A patent indicator should thus weigh the relevance and interactions of patent classification codes within the evolving technology. By improving measures of technological distance, we can more effectively recognize and leverage potential complementarities and synergies in innovation strategies. Appendix D includes a dynamic measure of technological distance.

A temporal model of technology emergence

Our results suggest a new perspective on the temporal dynamics underpinning technology emergence. On the one hand, studies on modalities conceptualize emergence as a focal event where the interaction between technological components has the potential to yield a new technological domain (Basalla, 1988; Cattani, 2006; Cattani & Mastrogiorgio, 2021; Fleming & Sorenson, 2004; Hargadon, 2003; Kodama, 1992; Levinthal, 1997). On the other, research on trajectories has explained links in time showing how technology emergence might follow specific paths that unfold linearly (path dependence) or are punctuated by radical shifts (punctuated equilibrium) (Anderson & Tushman, 1990; Tushman & Anderson, 1986; Utterback & Abernathy, 1975). Thus, while the studies on modalities have looked at the synchronic aspects of technology emergence, the research on trajectories has disentangled the diachronic issues.

Our model tracks the emergence of new technologies by showing both synchronic and diachronic evolutionary dynamics. Specifically, our review of the blockchain domain provides synchronic snapshots of the state of a given technology at different points in time from inception to later evolution. In each snapshot, our analyses have captured processes of self-organization driven by technology fitness and self-reinforcing mechanisms that portray micro-level interactions among technological elements. In the specific domain of blockchain, both technology fitness and self-reinforcing mechanisms played a crucial role. By connecting the different snapshots and expanding the timeframe, we have been able to observe changes in the mechanisms at work. Specifically, technology fitness allows more recent technological elements to increase their influence in the domain while self-reinforcing leads prominent technological elements to increase their influence over time. By providing a more holistic picture of the temporal structuring of technology, our study can help researchers understand what initial constraints based on the initial decisions taken by inventors might determine specific technological paths and enable a core structure to be identified in the technological domain (Arthur, 1994).

The temporal structuring of emerging technologies also has important consequences for predicting future developments of a technological trajectory. Our study has focused on the micro and macro dynamics of technology emergence in a technological domain that is still evolving. Based on our simulations, we identify three distinct evolutionary scenarios — non-emergence, lock-in, and emergence — in which the presence or absence of fitness and self-reinforcing mechanisms shape the structuring of a new technology. Specifically, technology fitness facilitates connections among diverse technological elements, increasing the complexity and the scope of technology, while the self-reinforcing mechanisms contribute to the formation of a technology core and the consolidation of technological trajectories.

These scenarios have important management implications because they can guide managers toward the adoption of a successful technology strategy. At this time, many innovators are struggling to contribute to the emergence of new domains. An example of this might be cultured meat technology, which is attracting substantial investment and encouraging the entrance of new players, including startups. Although the promise of a new market is there, however, the technological domain has not yet emerged. To make this happen, innovators should first attract new technological elements by borrowing them from other fields (such as plant-based meat), reinforcing successful procedures and technological patterns. In other words, to innovate effectively, firms need to assess emerging configurations of technology fitness and self-reinforcing and make informed decisions about how novel or conforming their technological innovations should be (Brewer, 1991; Zhao, Fisher, Lounsbury, & Miller, 2017).

Based on the outcomes of our simulations, we expect that technology is more likely to emerge when firms and innovators exercise agency in relation to the lacking mechanism. In a scenario of non-emergence, where technology fitness is the only mechanism being activated, innovators should concentrate their efforts on exploiting existing connections and helping crystallize the core domain, thus providing it with a stronger identity. Conversely, when self-reinforcing is being used in isolation, firms and innovators need to concentrate on fostering technology fitness, thus avoiding lock-in effects. Managers should thus aim for an 'optimal point' where their technological innovations are distinct enough to avoid lock-in effects but also sufficiently aligned with the core domain to ensure relevance and applicability (Hsu, Hannan, & Koçak, 2018; Zhao et al., 2017; Zuckerman, 2016;). In this case, innovators should experiment with other complementary domains, thereby increasing technological opportunities and expanding the scope of the technology. These considerations can also be read in terms of implementing a strategic balance between consolidating core technologies and fostering technological diversity (Hsu et al., 2018) concerning technology emergence since the value of an innovation is maximized either when extending its technological scope and opportunities in a technological domain or when investing in strategic activities close to the core of the domain. Finally, firms and innovators should also consider the agency of the technological elements themselves. This means understanding the inherent characteristics, strengths, and integration of the relevant technology and how they might influence and shape the domain.

CONCLUSION

As with any study, this work has some limitations that can set the stage for future research. First, we used patents to examine inventive activity in a particular domain. It has long been argued that not all inventions are patented because firms rely on secrecy (Leten, Belderbos, & Van Looy, 2016) or simply because some inventions are open source. This latter aspect is particularly relevant for the blockchain domain because the first Bitcoins were created in a collaborative open-source environment. Nevertheless, although it was not possible to track non-patent-related information, we might deduce that the patents included in our sample encompass key technology features at that specific time. To this extent, they can be considered to be representative of the overall knowledge of blockchain. Future studies should extend our understanding of the role of non-patent-related information in setting new technology patterns.

Second, this study employs patent co-classification to investigate emergence as a structuring process, focusing on the blockchain domain. Although this fine-grained lens is particularly suitable to capture technology dynamics and early-stage developments, future studies could utilize patent co-citation analysis (e.g., Jaffe, Henderson, & Trajtenberg, 1993; Jaffe & Rassenfosse, 2019) to measure and track the knowledge flows, and examine further evolutionary stages of the blockchain technology. Third, our results portray the formation of a technological core that acquires increasing complexity and broadens the scope of application. This points to the establishment of blockchain as a general-purpose technology (see, for example, Bresnahan & Trajtenberg, 1995; Goldfarb, Taska, & Teodoridis, 2023). Future studies might investigate these dynamics by empirically examining how and to what extent technology fitness and self-reinforcing mechanisms contribute to structuring a domain as a general rather than a narrowly structured objective. Third, this study does not account for market dynamics. Market feedback is fundamental for directing a firm's R&D efforts to satisfy customer needs. We have assumed that firms are willing to develop technologies that appear to be more promising, thereby allowing them to gain a competitive advantage. Future research might consider both technology and market forces to build a more comprehensive overview of the emergence and structuring of a technology domain. Finally, in line with prior recombination literature, our analysis is based on pairs of technological elements (Carnabuci & Operti, 2013; Fleming 2001; Fleming & Sorenson, 2001; 2004). We have assessed how their connections change over time and eventually create a specific trajectory. Although we have used the decomposability measure to assess technology structuring by accounting for a broader set of connections rather than direct connections, future research might examine trios or even larger elementary configurations to assess structural stability. Such an expansion might build upon our current findings, offering a more complex and nuanced understanding of technological domains.

This study contributes to our understanding of technology emergence by looking at the structuring processes by which technological elements progressively aggregate and crystallize into stable outcomes. In line with the tenets of complexity theory, our study assumes that technology is always in the process of becoming or turning into something different (Tsoukas, 2017). From this perspective, technology emergence is an interactive accomplishment that begins as an open-ended process and becomes progressively constrained by the boundaries of emerging technological patterns and self-reinforcing mechanisms. It is hoped that our findings will encourage future research on technology emergence aimed at testing and extending our theoretical insights across different technological domains.

REFERENCES

Abernathy, W. J., & Utterback, J. M. 1978. Patterns of industrial innovation. *Technology Review*, 80: 40–47.

Adner, R., & Kapoor, R. 2016. Right tech, wrong time. *Harvard Business Review*, *94*(11), 60-67.

Adner, R., & Levinthal, D. A. 2002. The emergence of emerging technologies. *California Management Review*, 45: 50–66.

Ahuja, G., & Katila, R. 2001. Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal*, 22: 197–220.

Anderson, P., & Tushman, M. L. 1990. Technological discontinuities and dominant designs: A cyclical model of technological change. *Administrative Science Quarterly,* 35: 604–633.

Arthur, W. B. 1994. *Increasing returns and path dependence in the economy*. University of Michigan Press.

Arthur, W. B., 1989. Competing technologies, increasing returns, and lock-in by historical events. *The Economic Journal,* 99: 116–131.

Bakker, S. 2010. The car industry and the blow-out of the hydrogen hype. *Energy Policy*, *38*(11), 6540-6544.

Bailey, D. E., Faraj, S., Hinds, P. J., Leonardi, P. M., & von Krogh, G. 2022. We are all theorists of technology now: A relational perspective on emerging technology and organizing. *Organization Science*, *33*(1), 1-18.

Basalla, G. 1988. *The evolution of technology*. Cambridge University Press.

Biais, B., Capponi, A., Cong, L. W., Gaur, V., & Giesecke, K. 2023. Advances in blockchain and crypto economics. *Management Science*, *69*(11), 6417-6426.

Blackmore, S. 2000. The meme machine (Vol. 25). Oxford Paperbacks.

Borzillo, S., & Kaminska-Labbé, R. 2011. Unravelling the dynamics of knowledge creation in communities of practice though complexity theory lenses. *Knowledge Management Research & Practice, 9*(4), 353-366.

Bresnahan, T. F., & Trajtenberg, M. 1995. General purpose technologies 'Engines of growth'?. *Journal of Econometrics,* 65: 83–108.

Brewer, M. B. 1991. The social self: On being the same and different at the same time. *Personality and Social Psychology Bulletin,* 17(5), 475-482.

Caldarelli, G., Capocci, A., De Los Rios, P., & Munoz, M. A. 2002. Scale-free networks from varying vertex intrinsic fitness. *Physical Review Letters, 89*(25), 258702.

Capaldo, A., Lavie, D., & Messeni Petruzzelli, A. 2017. Knowledge maturity and the scientific value of innovations: The roles of knowledge distance and adoption. *Journal of Management,* 43: 503–533.

Carnabuci, G., & Bruggeman, J. 2009. Knowledge specialization, knowledge brokerage and the uneven growth of technology domains. *Social Forces,* 88: 607–641.

Carnabuci, G., & Operti, E. 2013. Where do firms' recombinant capabilities come from? Intraorganizational networks, knowledge, and firms' ability to innovate through technological recombination. *Strategic Management Journal, 34*(13), 1591-1613.

Cattani, G. 2006. Technological pre-adaptation, speciation, and emergence of new technologies: how Corning invented and developed fiber optics. *Industrial and Corporate Change*, 15: 285–318.

Cattani, G., & Mastrogiorgio, M. (Eds.). 2021. *New developments in evolutionary innovation: Novelty creation in a serendipitous economy*. Oxford University Press.

Chen, Y., Pereira, I., & Patel, P. C. 2021. Decentralized Governance of Digital Platforms. *Journal of Management*, 47: 1305–1337

Clark, K. B. 1985. The interaction of design hierarchies and market concepts in technological evolution. *Research Policy*, 14: 235–251.

Clarke, N. S., Jürgens, B., & Herrero-Solana, V. 2020. Blockchain patent landscaping: An expert based methodology and search query. *World Patent Information*, *61*, 101964. DOI: 10.1016/j.wpi.2020.101964

Criscuolo, P., & Verspagen, B. 2008. Does it matter where patent citations come from? Inventor vs. examiner citations in European patents. *Research Policy*, 37: 1892–1908.

David, P. A. 1986. Understanding the economics of QWERTY: The necessity of history. *Economic History and the Modern Economics*, 30–49.

David, P. A. 1985. Clio and the Economics of QWERTY. *The American Economic Review*, 75: 332–337.

Devezas, T. C., & Corredine, J. T. 2002. The non-linear dynamics of technoeconomic systems: an informational interpretation. *Technological Forecasting and Social Change*, 69: 317–357.

Dick, P., Faems, D., & Harley, B. 2017. An introduction to the special issue on managing complexity within and across organizational boundaries. *Journal of Management Studies*, 54: 129–131.

Diestre, L., & Rajagopalan, N. 2012. Are all 'sharks' dangerous? Nnew biotechnology ventures and partner selection in R&D alliances. *Strategic Management Journal*, 33: 1115–1134.

Dosi, G. 1982. Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. *Research Policy*, 11: 147–162.

Engelsman, E. C., & van Raan, A. F. 1994. A patent-based cartography of technology. *Research Policy*, *23*(1), 1-26.

Evans, J. 2010. Industry collaboration, scientific sharing and the dissemination of knowledge. *Social Studies of Science*, 40: 757–791.

Fleming, L. 2001. Recombinant uncertainty in technological search. *Management Science*, 47: 117–132.

Fleming, L., & Sorenson, O. 2001. Technology as a complex adaptive system: evidence from patent data. *Research Policy,* 30: 1019–1039.

Fleming, L., & Sorenson, O. 2004. Science as a map in technological search. *Strategic Management Journal*, 25: 909–928.

Goldenfeld, N., & Kadanoff, L. P. 1999. Simple lessons from complexity. *Science*, 284: 87–89.

Goldfarb, A., Taska, B., & Teodoridis, F. 2023. Could machine learning be a general purpose technology? a comparison of emerging technologies using data from online job postings. *Research Policy*, *52*(1), 104653.

Goldstein, J. 1999. Emergence as a construct: History and issues. *Emergence*, 1: 49–72.

Gould, R. V. 2002. The origins of status hierarchies: A formal theory and empirical test. *American Journal of Sociology*, *107*(5), 1143-1178.

Greenwood, R., & Meyer, R. E. 2008. Influencing ideas: A celebration of DiMaggio and Powell (1983). *Journal of Management Inquiry*, *17*(4), 258-264.

Grigoriou, K., & Rothaermel, F. T. 2014. Structural microfoundations of innovation: The role of relational stars. *Journal of Management,* 40: 586–615.

Grodal, S., Gotsopoulos, A., & Suarez, F. F. 2015. The coevolution of technologies and categories during industry emergence. *Academy of Management Review,* 40: 423–445.

Grodal, S., Krabbe, A., & Chang-Zunino, M. 2023. The Evolution of Technology. *Academy of Management Annals*, 17(1), 141-180.

Haken, H. 1981. The science of structure: Synergetics. van Nostrand Reinhold Publishers.

Hargadon, A. 2003. *How breakthroughs happen: The surprising truth about how companies innovate*. Harvard Business Press.

Hargadon, A., & Sutton, R. I. 1997. Technology brokering and innovation in a product development firm. *Administrative Science Quarterly*, 716–749.

Harrigan, K. R., Di Guardo, M. C., Marku, E., & Velez, B. N. 2017. Using a distance measure to operationalise patent originality. *Technology Analysis & Strategic Management*, 29: 988–1001.

Henderson, R. M., & Clark, K. B. 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly*, 9–30.

Hsieh, Y. Y., & Vergne, J. P. 2023. The future of the web? The coordination and early-stage growth of decentralized platforms. *Strategic Management Journal*, *44*(3), 829-857.

Hsu, G., Hannan, M. T., & Koçak, Ö. 2018. Exploration and exploitation: The impact of organizational learning on community entry. *Administrative Science Quarterly*, 63(4), 708-744.

Iansiti, M., & Lakhani, K. R. 2017. The truth about blockchain. *Harvard Business Review,* 95: 118–127.

Kapoor, R., & Klueter, T. 2020. Progress and setbacks: The two faces of technology emergence. *Research Policy,* 49:103874.

Kaye, B., & Wagstaff, J. 2017. Bitcoin's "creator" races to patent technology with gambling tycoon, Reuters Investigates. https://www.reuters.com/investigates/special-report/bitcoin-wright-patents/

Khanna, R. 2022. Peeking Inside the Black Box: Inventor Turnover and Patent Termination. *Journal of Management*, *48*(4), 936-972.

Kher, R., Terjesen, S., & Liu, C. 2020. Blockchain, Bitcoin, and ICOs: a review and research agenda. *Small Business Economics*, 1–22.

Kodama, F. 1992. Technology fusion and the new R&D. *Harvard Business Review*, 70–78.

Kok, H., Faems, D., & de Faria, P. 2019. Dusting off the knowledge shelves: Recombinant lag and the technological value of inventions. *Journal of Management*, 45: 2807–2836.

Krapivsky, P. L., & Redner, S. 2001. Organization of growing random networks. *Physical Review E*, *63*(6), 066123.

Latour, B. 1987. *Science in action: How to follow scientists and engineers through society*. Harvard University Press.

Leten, B., Belderbos, R., & Van Looy, B. 2016. Entry and technological performance in new technology domains: Technological opportunities, technology competition and technological relatedness. *Journal of Management Studies*, 53, 1257–1291.

Levinthal, D. A. 1997. Adaptation on rugged landscapes. *Management Science*, 43: 934–950.

Levinthal, D. A. 1998. The slow pace of rapid technological change: gradualism and punctuation in technological change. *Industrial and Corporate Change*, 7: 217–247.

MacIntosh, R., & MacLean, D. 1999. Conditioned emergence: A dissipative structures approach to transformation. *Strategic Management Journal*, 20: 297–316.

Marin, A., Stubrin, L., & Van Zwanenberg, P. 2023. Technological lock-in in action: Appraisal and policy commitment in Argentina's seed sector. *Research Policy*, *52*(2), 104678.

Miller, D. 1982. Evolution and revolution: A quantum view of structural change in organizations. *Journal of Management Studies*, 19: 131–151.

Moehrle, M. G., & Caferoglu, H. 2019. Technological speciation as a source for emerging technologies. Using semantic patent analysis for the case of camera technology. *Technological Forecasting and Social Change*, 146: 776–784.

Morel, B., & Ramanujam, R. 1999. Through the looking glass of complexity: The dynamics of organizations as adaptive and evolving systems. *Organization Science*, *10*(3), 278-293.

Mowery, D. C., Oxley, J. E., & Silverman, B. S. 1998. Technological overlap and interfirm cooperation: implications for the resource-based view of the firm. *Research Policy*, 27: 507–523.

Nakamoto, S. 2008. A peer-to-peer electronic cash system. *Bitcoin. https://bitcoin. org/bitcoin. pdf*.

Nicolis, G. 1979. Irreversible thermodynamics. *Reports on Progress in Physics*, 42: 225.

Nicolis, G., & Prigogine, I. 1977. *Self-organization in non-equilibrium. systems*. New York, Wiley.

Nooteboom, B., Van Haverbeke, W., Duysters, G., Gilsing, V., & Van den Oord, A. 2007. Optimal cognitive distance and absorptive capacity. *Research Policy*, 36: 1016-1034.

Oberg, A., Korff, V. P., & Powell, W. W. 2017. Culture and Connectivity Intertwined: Visualizing Organizational Fields as Relational Structures and Meaning Systems☆. In *Structure, content and meaning of organizational networks: Extending network thinking* (pp. 17-47). Emerald Publishing Limited.

Park, M., Leahey, E., & Funk, R. J. 2023. Papers and patents are becoming less disruptive over time. *Nature*, *613*(7942), 138-144.

Pham, T., Sheridan, P., & Shimodaira, H. 2016. Joint estimation of preferential attachment and node fitness in growing complex networks. *Scientific Reports*, 6: 1–13.

Pham, T., Sheridan, P., & Shimodaira, H. 2020. PAFit: An R package for the non-parametric estimation of preferential attachment and node fitness in temporal complex networks. *Journal of Statistical Software*, 92: 1–30

Prigogine, I. 1980. *Form Being to Becoming: Time and Complexity in the Physical Systems*. W.H. Freeman and Company, New York.

Prigogine, I., & Stengers, I. 1984. *Order out of chaos: Man's new dialogue with nature*, Random House, New York.

Rosenkopf, L., & Almeida, P. 2003. Overcoming local search through alliances and mobility. *Management Science*, 49: 751–766.

Rosenkopf, L., & Nerkar, A. 2001. Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal*, 22: 287–306.

Sahal, D. 1985. Technological guideposts and innovation avenues. *Research Policy*, 14: 61–82.

Savage, J. P., Li, M., Turner, S. F., Hatfield, D. E., & Cardinal, L. B. 2020. Mapping patent usage in management research: The state of prior art. *Journal of Management*, 46: 1121–1155.

Schillebeeckx, S. J., Lin, Y., George, G., & Alnuaimi, T. 2021. Knowledge recombination and inventor networks: The asymmetric effects of embeddedness on knowledge reuse and impact. *Journal of Management*, 47: 838–866.

Schmeiss, J., Hoelzle, K., & Tech, R. P. 2019. Designing governance mechanisms in platform ecosystems: Addressing the paradox of openness through blockchain technology. *California Management Review*, 62: 121–143.

Simon, H. A. 1962. The architecture of complexity. *Proceedings of the American Philosophical Society*,106, 467–482.

Soete, L., & Freeman, C. 2012. *The Economics of Industrial Innovation*. Routledge.

Somaya, D., Teece, D., & Wakeman, S. 2011. Innovation in multi-invention contexts: Mapping solutions to technological and intellectual property complexity. *California Management Review*, *53*(4), 47-79.

Suarez, F. F. 2004. Battles for technological dominance: An integrative framework. *Research Policy*, 33: 271–286.

Sydow, J., & Schreyögg, G. 2013. *Self-reinforcing processes in and among organizations*. Springer.

Sydow, J., Schreyögg, G., & Koch, J. 2009. Organizational path dependence: Opening the black box. *Academy of Management Review*, 34: 689–709.

Sydow, J., Schreyögg, G., & Koch, J. 2020. On the theory of organizational path dependence: Clarifications, replies to objections, and extensions. *Academy of Management Review*, 45: 717–734.

Tapscott, D., & Tapscott, A. 2017. How blockchain will change organizations. *MIT Sloan Management Review*, 58: 10.

Teece, D. J. 2018. Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Research Policy*, *47*(8), 1367-1387.

Teece, D. J. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy*, 15: 285–305.

Thietart, R. A. 2016. Strategy dynamics: Agency, path dependency, and self-organized emergence. *Strategic Management Journal*, 37: 774–792.

Tijssen, R. J. 1992. A quantitative assessment of interdisciplinary structures in science and technology: co-classification analysis of energy research. *Research Policy*, *21*(1), 27-44.

Tsoukas, H. 2017. Don’t simplify, complexity: from disjunctive to conjunctive theorizing in organization and management studies. *Journal of Management Studies*, 54: 132–153.

Tushman, M. L., & Anderson, P. 1986. Technological discontinuities and organizational environments. *Administrative Science Quarterly*, 439–465.

Tushman, M. L., Romanelli, E. 1985. Organizational evolution: A metamorphosis model of convergence and reorientation. *Research in Organizational Behavior*, 7: 171–222.

Utterback, J. M., & Abernathy, W. J. 1975. A dynamic model of process and product innovation. *Omega*, 3: 639–656.

Wang, F. 2024. Does the recombination of distant scientific knowledge generate valuable inventions? An analysis of pharmaceutical patents. *Technovation*, *130*, 102947. Doi: 10.1016/j.technovation.2023.102947

Wang, C., Rodan, S., Fruin, M., & Xu, X. 2014. Knowledge networks, collaboration networks, and exploratory innovation. *Academy of Management Journal*, 57: 484–514.

Wang, T., & Chen, Y. 2018. Capability stretching in product innovation. *Journal of Management*, 44: 784–810.

Xiao, T., Makhija, M., & Karim, S. 2022. A knowledge recombination perspective of innovation: review and new research directions. *Journal of Management*, *48*(6), 1724-1777.

Yayavaram, S., & Ahuja, G. 2008. Decomposability in knowledge structures and its impact on the usefulness of inventions and knowledge-base malleability. *Administrative Science Quarterly*, 53: 333–362.

Yoruk, E., Radosevic, S., & Fischer, B. 2023. Technological profiles, upgrading and the dynamics of growth: Country-level patterns and trajectories across distinct stages of development. *Research Policy*, *52*(8), 104847. Doi: 10.1016/j.respol.2023.104847.

Zhao, E. Y., Fisher, G., Lounsbury, M., & Miller, D. 2017. Optimal distinctiveness: Broadening the interface between institutional theory and strategic management. *Academy of Management Annals*, 11(1), 733-772.

Zuckerman, E. W. 2016. Optimal distinctiveness revisited: An integrative framework for understanding the balance between differentiation and conformity in individual and organizational identities. *Journal of Management Studies*, 53(4), 629-659.

Table 1

Patent search query

Queries		Patent families
Q1	(blockchain or block ADJ chain) OR CTB=(blockchain or block ADJ chain)) AND CTB=((hash near3 point*) or (link* near3 blocks) or (timestamp and transact*) or (Cryptography or cryptology) or ((record* near3 transact*) same (across* and (multiple or computers or devices or terminal*))) or e-cash or *currenc* or Bitcoin or Ethereum or Ripple or Litecoin or digital ADJ token);	620
Q2	((distribut* ADJ ledger*) or ((distribut* near3 data*) and ((store* or accross*) near5 multiple))) OR CTB=((distribut* ADJ ledger*) or ((distribut* near3 data*) and ((store* or accross*) near5 multiple)))) AND CTB=(decentral* or Consensus ADJ algorithm or blockchain or block ADJ chain or (comput* same (dispersed near5 network*) same (intercon* or connect*)) or (peer adj2 peer));	758
Q3	((((smart ADJ contract*) and agreement) or (enforced near3 without near3 interaction) or (automated ADJ escrow)) or ((protocol* or Consensus ADJ algorithm) near5 (agreement and transaction))) OR CTB=((((smart ADJ contract*) and agreement) or (enforced near3 without near3 interaction) or (automated ADJ escrow)) or ((protocol* or Consensus ADJ algorithm) near5 (agreement and transaction)));	161
	Q1 or Q2 or Q3 (duplicates removed)	1,388

Table 2

Estimation of self-reinforcing and technology fitness mechanisms

	Model 1	Model 2
α exponent	0.923	0.907
Confidence interval 95%	[0.880; 0.965]	[0.876; 0.937]

Figure 1

The process of technology emergence

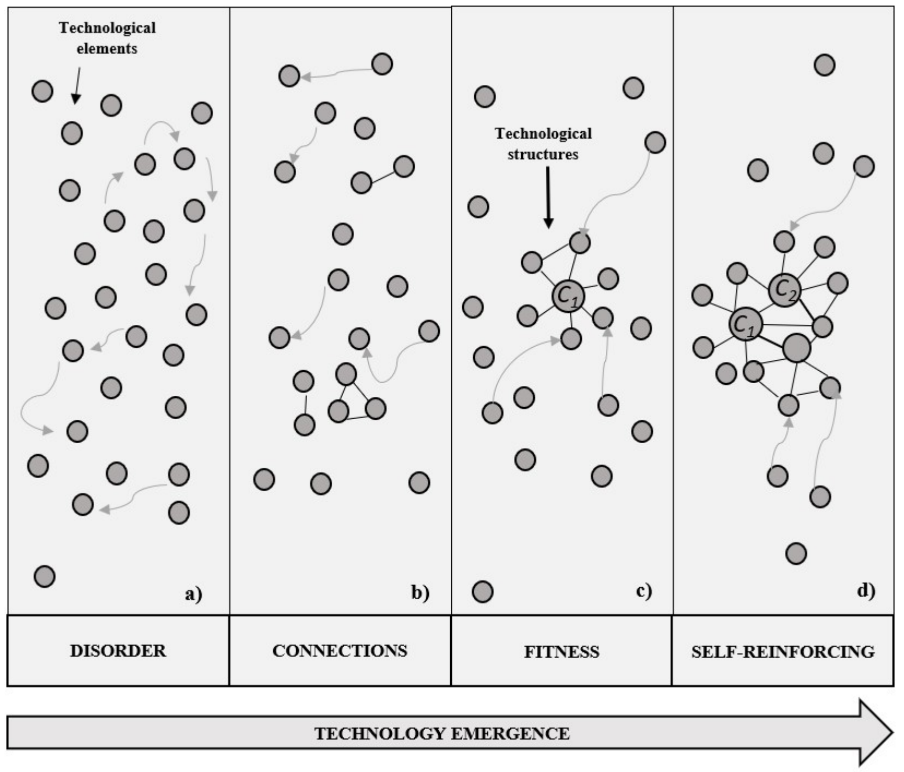
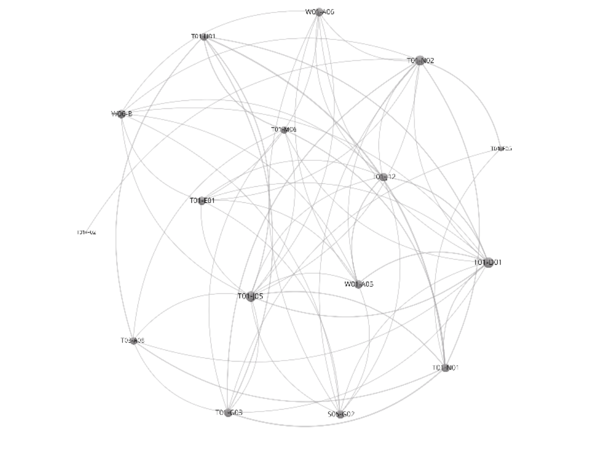
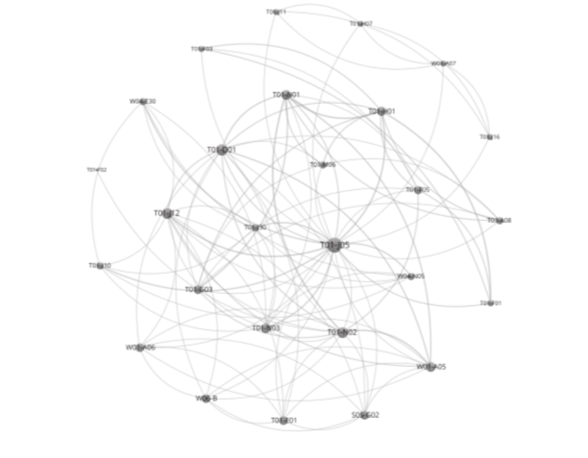
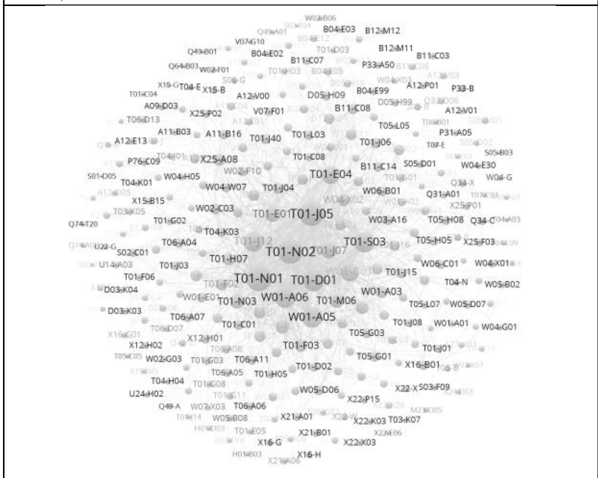


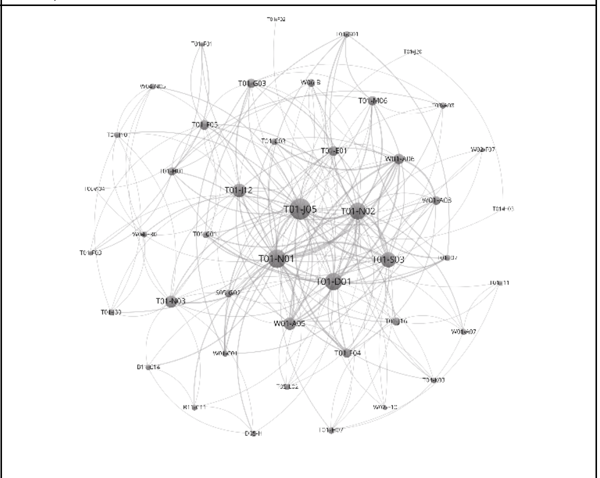
Figure 2

The structuring of the blockchain domain

I)	**2009-2010**
	
No. patents: 5 No. tech. elements: 16 No. connections: 134 **Decomposability measure:** 0.605	**<u>Highest connected tech. elements</u>** 1) T01-D01: 16 connections 2) T01-J05: 14 connections 3) T01-N02: 12 connections 4) T01-J12: 10 connections 5) W01-A05: 10 connections 6) T01-G03: 9 connections 7) T01-N01: 9 connections 8) S05-G02: 8 connections 9) T01-E01: 8 connections 10) W01-A06: 8 connections

II)	**2009-2012**
	
No. patents: 12 No. tech. elements: 27 No. connections: 216 **Decomposability measure:** 0.809	**<u>Highest connected tech. elements</u>** 1) T01-J05: 28 connections (+12) 2) T01-D01: 16 connections (+0) 3) T01-J12: 16 connections (+6) 4) T01-N02: 12 connections (+0) 5) T01-H01: 10 connections (+4) 6) W01-A05: 10 connections (+0) 7) T01-G03: 9 connections (+0) 8) T01-N01: 9 connections (+0) 9) T01-E01: 8 connections (+0) 10) W01-A06: 8 connections (+0)

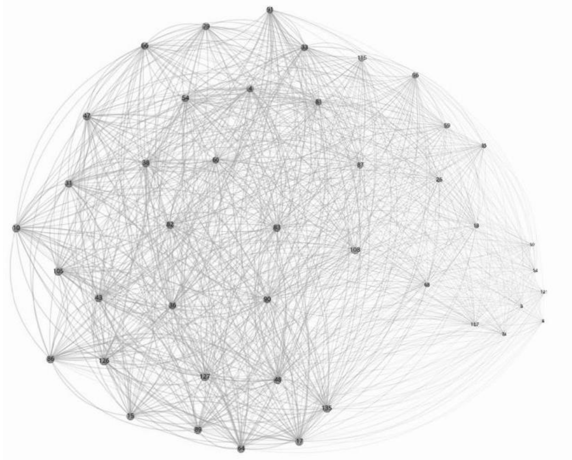
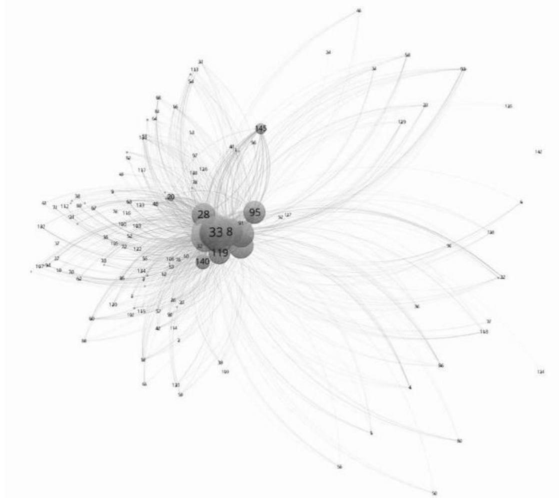
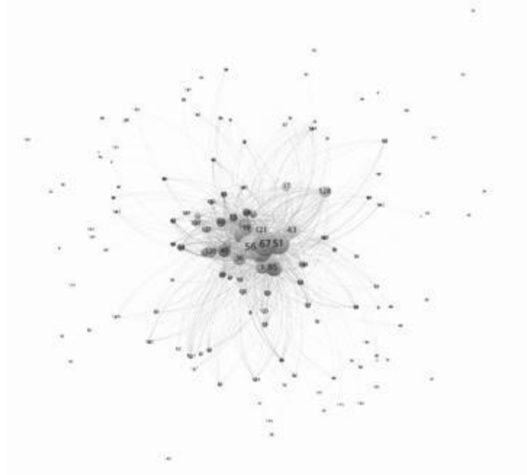
IV)	**2009-2020**
	
No. patents: 1,388 No. tech. elem: 287 No. connect.: 27,780 **Decomposability measure:** 0.922	**<u>Highest connected tech. elements</u>** 1) T01-J05: 3,519 connections (+3,443) 2) T01-N01: 3,208 connections (+3,124) 3) T01-N02: 2,917 connections (+2,855) 4) T01-D01: 2,811 connections (+2,747) 5) T01-S03: 1,632 connections (+1,572) 6) T01-J12: 1,552 connections (+1,521) 7) W01-A05: 1,470 connections (+1,427) 8) W01-A06: 1,113 connections (+1,083) 9) T01-E04: 922 connections (+900) 10) W01-C01: 522 connections (+516)

III)	**2009-2015**
	
No. patents: 41 No. tech. elements: 45 No. connections: 746 **Decomposability measure:** 0.813	**<u>Highest connected tech. elements</u>** 1) T01-N01: 84 connections (+75) 2) T01-J05: 76 connections (+48) 3) T01-D01: 64 connections (+48) 4) T01-N02: 62 connections (+50) 5) T01-S03: 60 connections (+60) 6) W01-A05: 43 connections (+33) 7) T01-J12: 31 connections (+15) 8) W01-A06: 30 connections (+22) 9) T01-E04: 22 connections (+22) 10) W01-A03: 22 connections (+22)

DESCRIPTION OF THE PATENT CLASSIFICATION CODES (ordered alphabetically)	
S05-G02: Medical and Digital Health systems, hospital equip.	T01-J12: Program management, GUI/WIMPS/HCI
T01-D01: Data Encryption and Decryption	T01-N01: Internet and information transfer - applications
T01-E01: Sorting, selecting, merging, or comparing data	T01-N02: Communications and control
T01-E04: Comparing digital values; random number generators	T01-S03: Claimed software products
T01-G03: Using redundancy in operation or hardware	W01-A03: Multiple use of transmission path
T01-H01: Interconnections to Random Access Memory (RAM)	W01-A05: Secret communication
T01-J05: Data processing systems for administration, commerce, or information retrieval	W01-A06: Exchanges; connections between exchanges
	W01-C01: Telephony - Subscriber equipment

Figure 3

Simulations

S1: Only technology fitness is present	S2: Only self-reinforcing mechanism is present	S3: Both mechanisms are present
		

APPENDIX A

Calculation of the decomposability measure

This appendix applies the decomposability measure to a hypothetical example of technological structuring. Let's consider a simple structure composed of four technological elements and let's suppose they belong to the hydrogen fuel cell technology: Electrolysis Systems (A), Storage Materials (B), Membrane Materials (C), and Control Systems (D). Table 1A includes a summary of the parameters and their descriptions.

Table 1A

Summary of the data used in the example

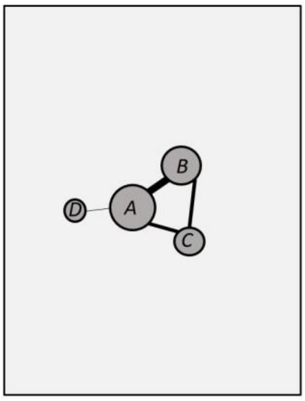
	Parameter	Description	Values	Explanation
1	Technological element	Technological elements that compose the technology structure	{A, B, C, D}	A, B, C, and D represent unique technological elements in the technological domain.
2	Frequency of connections	Number of connections between technological elements	$w(A, B) = 7$ $w(A, C) = 3$ $w(B, C) = 2$ $w(A, D) = 1$ $w(B, D) = 0$ $w(C, D) = 0$	*w* ranges between 0 and potentially infinite and quantifies the number of connections between two technological elements. A value of zero indicates no direct connections.

3	Relative size of nodes	The relative number of occurrences of a technological element compared to the total number of occurrences	$z(A)$=0.42 $z(B)$=0.35 $z(C)$=0.19 $z(D)$=0.04 The total number of occurrences of technological elements is 26	z ranges between 0 and 1 and represents the relative number of occurrences of a technological element compared to the total number of occurrences. It is a metric of the importance of a technological element in the technological domain. For instance, a relative size z(A)=0.42 means that the technological element Electrolysis Systems (A) has a predominant role given the highest number of occurrences.

The Electrolysis Systems (A) is the most prevalent technological element given its foundational role in hydrogen production. Storage Materials (B) is less prevalent in the technological domain since it primarily relates to the storing of hydrogen. Membrane Materials (C) plays a significant role in hydrogen fuel cell technology as it is crucial for the operation of the fuel cell. Lastly, Control Systems (D) is relevant to the technological field, but it plays a more marginal role. Figure 1A depicts the technological elements and their role within the hydrogen fuel cell technology domain.

Figure 1A

The technological structure as in the example of the hydrogen fuel cell technology



To proceed with the calculation of the decomposability measure, we first consider the microstructure of Electrolysis Systems (A) n_A, which includes its direct connections with Storage Materials (B), Membrane Materials (C), and Control Systems (D), as well as the number of all possible connections across them {A, B, C, D} that consist of A-B, A-C, A-D, B-C, B-D, and C-D, as represented in the denominator of the formula for the cv_A. The threshold connection value for n_A, denoted as cv_A, is calculated as:

$$cv_A = \frac{w(A,B)+w(A,C)+w(A,D)}{6} = \frac{7+3+1}{6} = 1.83$$

Given cv_A, equal to 1.83, both connection patterns between Electrolysis Systems (A) and Storage Materials (B), as well as Electrolysis Systems (A) and Membrane Materials (C) are identified as strong. Conversely, the connection pattern between Electrolysis Systems (A) and Control Systems (D) is identified as weak. This results in an integration level $I_A = \frac{1}{6} = 0.167$ for n_A.

We now consider Storage Materials (B) n_B as the focal technological element, and its direct connections with both Electrolysis Systems (A) and Membrane Materials (C), as well as all possible connections across the microstructure {A, B, C}. The threshold connection value for n_B is:

$$cv_B = \frac{w(A,B)+w(B,C)}{3} = \frac{7+2}{3} = 3$$

Given cv_B, the connection pattern between Storage Materials (B) and Electrolysis Systems (A) is strong, while Storage Materials (B) and Membrane Materials (C) is weak. This results in an integration level $I_B = \frac{1}{3} = 0.33$ for n_B.

Membrane Materials (C), n_C has direct connections with Electrolysis Systems (A) and Storage Materials (B). We consider these direct connections and the possible connections between the technological elements within the microstructure {A, B, C}. The threshold connection value for n_C, is calculated as:

$$cv_C = \frac{w(A,C)+w(B,C)}{3} = \frac{3+2}{3} = 1.67$$

Considering cv_C is equal to 1.67, the connection patterns between both Membrane Materials (C) and Electrolysis Systems (A), as well as Membrane Materials (C) and Storage Materials (B), are strong. Thus, the integration level is $I_C = \frac{0}{3} = 0$ for Membrane Materials (C).

Finally, since the integration level for technological element D n_D is $I_D = 1$, we have all the necessary information to calculate the decomposability measure:

$$D = 1 - [z(A) \times I_A + z(B) \times I_B + z(c) \times I_C + z(D) \times I_D]$$

$$D = 1 - [0.42 \times 0.167 + 0.35 \times 0.33 + 0.19 \times 0 + 0.04 \times 1]$$

$$D = 1 - 0.226 = 0.774$$

The decomposability measure of 0.774 indicates a nearly decomposable structure characterized by both strong and weak connections. This points to an initial core formed by technological elements A, B, and C.

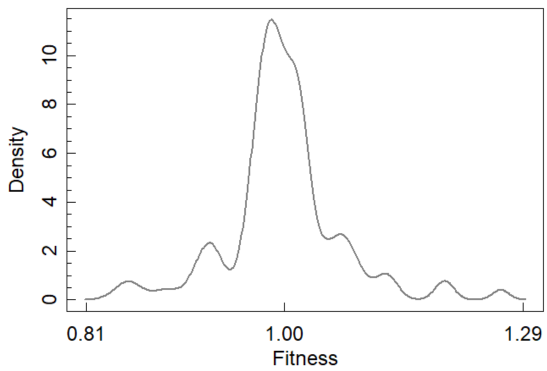
APPENDIX B

Estimating technology fitness and self-reinforcing mechanisms

Figure 1B shows the estimated distribution of the technology fitness mechanism for blockchain technology. It features a density plot that illustrates the distribution of the technology fitness values (η_i) across technological elements. This result shows a discernible pattern where the technology fitness values vary significantly, highlighting the heterogeneity among blockchain elements. This finding aligns with our theoretical framework and the results of the structuring of the blockchain domain, revealing variations that range from 0.81 to 1.29.

Figure 1B

Estimated distribution of technology fitness

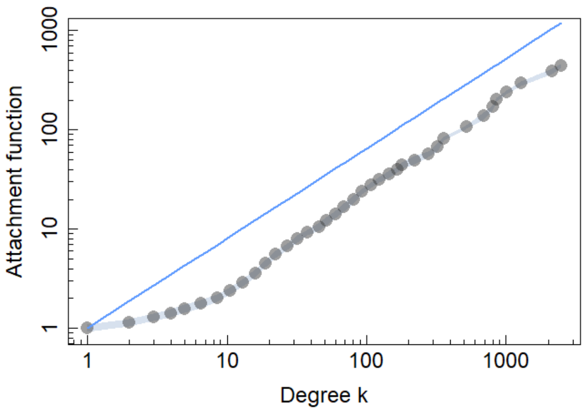


Notably, the peak of the distribution close to a value of 1 indicates that a majority of technological elements have a similar quality to connect with other technological elements, indicating a relatively balanced interconnected structure within blockchain technology. However, the elongated right tail demonstrates that some technological elements have successfully leveraged the technology fitness mechanism, enabling them to connect with various technological elements. This is the case of technological elements such as T01-J05 (Data processing systems for administration, commerce, or information retrieval) and T01-D01 (Data encryption and decryption), T01-J07 (Data processing systems for industrial process control), with values 1.29, 1.19, and 1.83 respectively. These values reflect their enhanced attractiveness, confirming their pivotal role within blockchain technology. Conversely, there exist a few technological elements that present values lower than 1. These values signify a relative lack of attractiveness, possibly indicative of their underdevelopment or emerging status in the technological domain. Understanding these differences is thus crucial to better comprehending the dynamic evolution and structuring of technology structuring.

Furthermore, Figure 2B shows a log-log plot where the self-reinforcing mechanism (A_k) and the number of connections (k) of technological elements are expressed in a logarithmic scale. The straight line indicates the linear case α=1[5]and is visualized as a reference point for comparison. In the case of blockchain technology, results indicate an α<1. This means that although technological elements with more connections are still more likely to gain new ones, the rate of gaining these connections increases more slowly than their number of connections (k). This implies that technological elements that are less connected have a relatively higher chance of gaining connections than would be expected if the relationship were linear (α=1).

Figure 2B

Estimation of the self-reinforcing mechanism ($A_k = k^{\alpha}$)



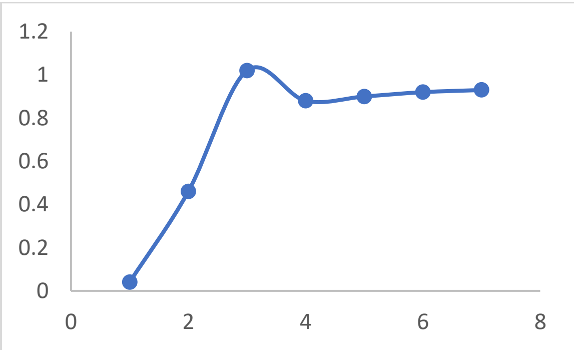
Smaller and less connected technological elements are thus not completely overshadowed by the larger and more connected ones. This understanding of connection dynamics in the blockchain domain is essential for appreciating the potential of emerging technological elements within this field.

[5] The linear case refers to a power-law relationship.

Finally, Figure 3B shows the results of a rolling procedure that estimates the α exponent of the self-reinforcing mechanism ($A_k = k^{\alpha}$) through a six-year rolling window (time cycles on the x-axis). This technique is used to illustrate the variations of the self-reinforcing mechanism over time. An increase in the α exponent signals that some technological elements have leveraged the self-reinforcing mechanism, allowing them to further increase their influence in blockchain technology. After the third cycle (2011-2016), the α exponent seems to reach a plateau, with values lower than 1, ranging between 1.88 in the fourth cycle and 0.93 in the seventh cycle. This observed stabilization of the α exponent suggests the emergence of a pattern within blockchain technology, influencing how new technological elements connect to each other. It is important to point out that when we observe an α exponent of blockchain technology that is stabilizing, this does not mean that the domain is no longer evolving. Rather, it indicates a situation in which the core technological elements are established, making blockchain technology more predictable for future technological developments.

Figure 3B

Rolling estimates of α exponent under $A_k = k^{\alpha}$ using a 6-year window



APPENDIX C

Simulating dynamics of technology emergence

In our theoretical model, the mechanisms of technology fitness and self-reinforcing serve as preconditions for emergence. Both mechanisms grow non-linearly and their predominance may shift over time. This simulation-based analysis aims to offer evidence of variations in technology emergence, which could potentially be applied to any technology domain. For this reason, technological elements are numerically labeled and do not refer to any patent classification codes.

In our model, the initial state acts as the foundation for the emerging network of technological elements and their connections. The initialization of the network is formalized as $G_0 = (V_0, E_0)$, where G_0 represents the initial state of the network, V_0 denotes the set of technological elements, which correspond to the technological classes of the first patent—randomly chosen between 5 and 8 because this interval is set by empirically examining the blockchain patent dataset—and E_0 is the set of connections representing the initial connections between technological elements.

As the simulation progresses, new patents are introduced. Each step of the simulation consists of adding one patent, which is associated with a set of technological elements. These technological elements are selected based on specific probabilities $P_i(t)$ affected by the two mechanisms technology fitness (η_i) and self-reinforcing ($A_k = k^\alpha$) formalized as $P_i(t) \propto A_{ki(t)} \times \eta_i$. (see Appendix B).

At each time step t, a new patent is introduced combining a set of technological elements C_t, which are selected based on the probabilities $P_i(t)$ previously defined. The new structure is updated as follows:

$$V_t = V_{t-1} \cup C_t \tag{1c}$$

$$E_t = E_{t-1} \cup \{(i, j) \mid i, j \in C_t, i \neq j\}$$

where V_t denotes the set of technological elements at time t, E_t represents the set of connections at time t, and C_t is the set of technological classes introduced at time t. New patented inventions might form either new connections with new technological elements that enter the domain or enforce existing connections. The entire process is dynamic and evolves over time. The network grows, becoming more intricate as technological elements interact in diverse configurations.

The simulation spans 1,388 iterative cycles, each introducing a patent to the technology domain. Technological class "co-occurrences" within patents are tracked through a matrix A. A_{ij} denotes how often technological elements n_i and n_j co-occur in the patents. A_{ij} is updated as new patents are added. The domain at any time t can be visualized as a graph with technological elements and connections weighted according to the metrics derived from matrix A. The weight of a connection between technological elements n_i and n_j at time t can be defined as $w_{ij}(t) = A_{ij}(t)$.

APPENDIX D

A dynamic measure of technological distance

The distance between two patents can be assessed using a dynamic technological distance (DTD) to account for the specific domain each patent is encompassed. Specifically, we account for the connections between technological elements and how these connections change over time. DTD is a measure that compares two patents, and it is calculated as follows:

$$\text{DTD}\ (P1, P2, t) = \sum_{i=1}^{N} w_{it} \text{ x } \delta\ (P1i, P2i) \quad (1d)$$

Where $p1$ and $p2$ are two patents being compared, t is the specific year of comparison, and N is the total number of distinct patent classification codes between the two patents. w_{it} is the weight of the i^{th} patent classification code in year t. This weight reflects the importance (i.e., degree of centrality) of the classification code within the domain for that year. δ ($P1_i$, $P2_i$) is the difference function for the i^{th} classification code between patents $P1$ and $P2$. It outputs 0 if both patents have that specific classification code, and 1 if only one has it.

Finally, a lower DTD value indicates the patents are more technologically similar within the context of the domain's dynamics for that year. A higher DTD suggests more significant technological differences. The dynamic weighting ensures the measure reflects the evolving domain importance of different technological elements. This indicator takes a more granular and dynamic approach than static patent indicators.