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VALIDATED FRAMEWORK REGARDING ENABLING TECHNOLOGIES OF INNOVATION ECOSYSTEM EMERGENCE IN INDUSTRY 4.0

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ABSTRACT

The shift from competition between products or firms to ecosystem competition requires a deeper understanding of the emergence of technologies. The perspective of innovation ecosystems considers the development of technologies based on prior innovations, and therefore allows us to predict technology development based on the trajectories of existing products. We present a novel patent-based framework for early detection of enabling technologies in ecosystems. We test the framework on the case of the emergence of industry 4.0, and therefore establish a theoretical definition of industry 4.0, which we operationalize using longitudinal patent data. In this context, our analysis confirms that the surge of industry 4.0 innovation has stabilized on a high level. Through an exploratory patent citation analysis, we also detect an expansion of industry 4.0 into areas formerly occupied by managers. We observe that industry 4.0 has reached a mature state of development. More importantly, however, our validated framework for forecasting enabling technologies of innovation ecosystem emergence permits the identification and prediction of subsequent, complementary technologies.

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1. INNOVATION ECOSYSTEMS EMERGENCE

Digital technologies may compete or complement other technologies depending on the context in which they evolve (Denicolai et al., 2021; Granstrand & Holgersson, 2020). Therefore, to understand the progress of one innovation, we must consider the ecosystem in which it is embedded (Adner & Kapoor, 2016; Baldwin et al., 2024). In innovation ecosystems, innovations evolve based on an existing technology landscape (Basalla, 1988). A disruption occurs when an innovation is applied to a new domain, and therefore commences a distinct technological trajectory (Levinthal, 1998). Hence, an innovation which is not disruptive to its original domain may spawn radical innovation when horizontally transferred to another domain (Carignani et al., 2019). It then becomes a platform upon which other innovations build (Autio & Thomas, 2014). Thus, as technologies mature, some of them enable the development of new technologies or of entire ecosystems (Nylund et al., 2024; Nylund et al., 2022, Teece, 2018). The relationships between technologies therefore explain the growth of the ecosystem as such.

The evolving nature of innovation ecosystems means that enabling technologies span from prior innovations. In this report, we ask whether the future trajectories of enabling technologies can be predicted based on the technologies on which they are based. We rely on theory on innovation ecosystems to devise a framework for the identification of enabling technologies, based on the trajectories between innovations manifest in patent citations (Choi & Park, 2009). The proposed framework is validated using data from the industry 4.0 innovation ecosystem. Finally, we discuss the implications of this work for theory and practice.

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2. ENABLING TECHNOLOGIES

Digital technologies may compete or complement other technologies depending on the context in which they evolve (Denicolai et al., 2021; Granstrand & Holgersson, 2020). Therefore, to understand digital transformation, we must consider the ecosystems in which innovations are embedded (Adner & Kapoor, 2016: Dąbrowska et al., 2022). In innovation ecosystems, innovations evolve based on an existing technology landscape (Basalla, 1988). A disruption occurs when an innovation is applied to a new domain, and therefore commences a distinct technological trajectory (Levinthal, 1998). Hence, an innovation which is not disruptive to its original domain may spawn radical innovation when horizontally transferred to another domain (Carignani et al., 2019). It then becomes a platform upon which other innovations build (Autio & Thomas, 2014). Thus, as technologies mature, some become platforms and enable the development of new technologies or of entire ecosystems (Nylund et al., 2022, Teece, 2018). The relationships between technologies therefore explain the growth of the ecosystem as such.

The evolving nature of innovation ecosystems means that enabling technologies span from prior innovations. In this report, we ask whether the future trajectories of enabling technologies can be predicted based on the technologies on which they are based. We rely on theory on innovation ecosystems to devise a framework for the identification of enabling technologies, based on the trajectories between innovations manifest in patent citations (Choi & Park, 2009). The proposed framework is validated using data from the industry 4.0 innovation ecosystem. Finally, we discuss the implications of this work for theory and practice.

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3. INDUSTRY 4.0

We validate the proposed framework by applying it to the empirical setting of industry 4.0. Industry 4.0 has been identified as a watershed in technological trajectories (Yu & Yan, 2022). The term industry 4.0 itself emerged from the "High-Tech Strategy" of the German government. It has ever since been used interchangeably with the fourth industrial revolution and is focused on digitally integrating processes and machines (Xu et al., 2018). While the "Industry 4.0" agenda has received the most international attention, similar initiatives outside of the German context exist such as China's "Made-in-China 2025" and (Li, 2018) Japan's Society 5.0 (Holroyd, 2022) initiatives. This concept of bringing together the digital and physical worlds will create intelligent production sites, smart products, new business models and will better integrate customers (Pereira & Romero, 2017). Though the industry 4.0 concept was initially to a large extent practice-driven and technology-oriented, it has diffused into academia. However, "Researchers and companies hold different points of view about the Industry 4.0 concept and visions" (Pereira & Romero, 2017).

Hermann *et al.* (2015) describe industry 4.0 with six design principles: interoperability, virtualization, decentralization, real-time capability, service orientation, and modularity. This transformation is enabled by an ever-expanding portfolio of technologies, including Cyber-physical systems, the Internet of things, cloud computing, big data, advanced robotics, augmented reality, simulation, additive manufacturing, blockchain, artificial intelligence and 5G (Alcácer & Cruz-Machado, 2019; Bigliardi et al., 2020; Bodkhe et al., 2020; Xu et al., 2018). At its core "industry 4.0 defines a methodology to generate a transformation from machine dominant manufacturing to digital manufacturing" (Oztemel & Gursev, 2020).

Hence the driving technology underlying the concept of industry 4.0 is the concept of Cyber-Physical Systems (CPS) (Lee et al., 2015; Maier et al., 2015). These systems are described as combinations of embedded systems and global networks (Rajkumar et al., 2010). Kagermann et al. (2013, p. 5) describe CPS as follows: "In the manufacturing environment, these Cyber-Physical Systems comprise smart machines, storage systems and production facilities capable of autonomously exchanging information, triggering actions and controlling each other independently", which enables interconnected companies to delicate capacities and orders automatically (Ghobakhloo, 2018).

Notably, this intra- and cross-company intelligence integration (Kagermann et al. 2011) does not only reshape the manufacturing process but also enables business model innovation (Mueller et

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al., 2018). For example, industry 4.0 technologies underly much recent development in business models based on green and sustainable technologies (Najmaei & Sadeghinejad, 2023).

Given this increase in complexity and interdependency of company interactions (Yang et al., 2022), the supply chain view must be abandoned in favor of an ecosystem approach (Benitez et al., 2020). Since the resulting ecosystem of interconnected actors jointly creates customer facing value, we will employ an innovation ecosystem (Jacobides et al., 2018) view throughout this report.

To streamline these complex interdependencies between different actors, the development of standards such as dominant designs is crucial in an innovation ecosystem (Miller & Toh, 2022). In addition, "dominant designs drive structures of investment in resources, capabilities, and complementary innovations that reach far beyond the single firm" (Brem & Nylund, 2024). Especially in the setting of industry 4.0 the development of a reference architecture is imperative, since "Industrie 4.0 will involve networking and integration of several different companies through value networks. This collaborative partnership will only be possible if a single set of common standards is developed. A reference architecture will be needed to provide a technical description of these standards and facilitate their implementation." (Kagermann *et al.,* 2013, p.6)

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4. FRAMEWORK FOR ENABLING TECHNOLOGIES OF ECOSYSTEM EMERGENCE

4.1. DATA

Patent data is useful to analyze wider networks of innovations (Stuart, 1999). We combine longitudinal patent data from the OECD REGPAT and OECD Citations databases regarding patents filed at the European Patent Office (EPO). The data spans a time period of 30 years, and such long time series allow for conservative forecasts by avoiding temporary effects (Armstrong et al., 2015). Patent counts of EPO patents are better indicators of innovative performance compared to similar patents from the United States Patent and Trademark Office (USPTO) (Geerts et al.,2018; Jaffe & Lerner, 2004) due to the higher patenting costs of the EPO (Van Pottelsberghe de la Potterie & François, 2009), lower work-load of patent examiners, and lower patent-granting rates (Quillen & Webster, 2001). The citation patterns of EPO patents are also more focused. EPO patents tend to cite about a third as many patents as US patents, (Michel & Bettels, 2001) since EPO aims to include only the most important documents (Webb et al., 2005).

4.2. METHOD

The detection of enabling technologies poses a conundrum for researchers: Early forecasts tend to be less accurate. On the other hand, once estimates are sufficiently accurate, it may be too late for managerial action (Lenz, 1985). The solution is to make very early evaluations and update as new information becomes available (Porter, 1991). A crucial challenge of early forecasts is the identification of enabling technologies or the detection of weak signals (Ansoff, 1975). Qualitative methods e.g., Delphi-based scenario analysis rely on the knowledge of experts to identify early technologies and thus depend on involving the right experts in order to obtain reliable predictions (Rowe & Wright, 1999). Patent-based methods have been developed for studying technology evolution processes (Kumar et al., 2021). They have been used for discerning technologies of particular importance e.g., general purpose technologies (Feldman & Yoon, 2012), but require that technologies achieve an impact prior to identification. However, capturing technologies at the initiation stage would enable a more adequate assignation of resources.

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We device a new framework for ecosystems, as outlined earlier, to identify paths from mature technologies to new trajectories. The proposed framework is depicted in Figure 1.

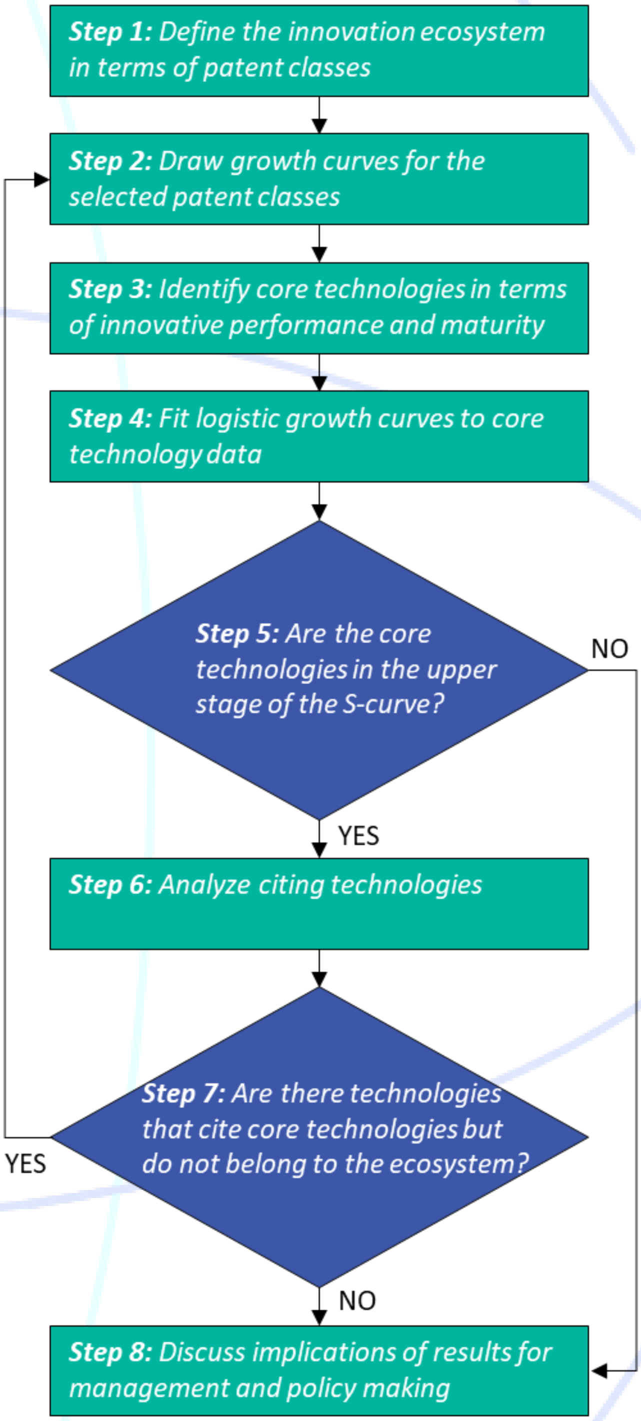

Figure 1. Proposed framework for forecasting enabling technologies of ecosystem emergence

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In step 1 of the proposed framework, we define the innovation ecosystem in terms of patent classes. We use prior theory for this definition, but if there are no existing studies to rely on, the researcher may have to engage in e.g., constructing an ontology for the innovation ecosystem in order to determine the relevant patent classes (Trappey et al.,2016). In step 2, we draw growth curves for the selected patent classes in terms of innovative performance, measured as the patenting frequency of each patent class, and calculated as the number of patent applications in a given year (Ahuja & Katila, 2001, Hall & Ziedonis, 2001; Keil et al., 2008; Stuart, 2000). The growth curve is one of the most prominent models that management theory has inherited from the study of natural ecosystems (Pearl, 1925). Such curves have previously been used to model patent production (Rusek et al., 2023). In step 3, we identify core technologies in terms of innovative performance and maturity through analyzing the growth curves. In step 4, we fit logistic growth curves to core technology data, since in the study of technology growth within ecosystems, we expect the innovative performance to assume a symmetric sigmoid shape without a known upper limit. In step 5, we verify whether the core technologies are in the upper stage of the sigmoid shape. If the core technologies are in the upper stage of the S-curve, we continue the analysis with step 6. If they are not, we proceed to the discussion in step 8. In step 6, we analyze the citing technologies through establishing which patent classes most frequently cite the core technologies. In step 7, we verify whether there are technologies that cite core technologies, but do not belong to the ecosystem, as defined in step 1. If there are, we recursively analyze those technologies by returning to step 2. If not, we proceed to the discussion in step 8. Finally, we discuss the validated framework and its implications for management and policy making.

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5. EMPIRICAL VALIDATION OF THE FRAMEWORK IN INDUSTRY 4.0

STEP 1. DEFINE THE INNOVATION ECOSYSTEM IN TERMS OF PATENT CLASSES

We study the industry 4.0 ecosystem using the proposed framework for forecasting enabling technologies. We first define the innovation ecosystem in terms of patent classes as per step 1 in the framework. The core technology underlying the concept of industry 4.0 is cyber-physical systems (Lee et al., 2015). We therefore begin our definition with the top ten IPC patent classes of cyber-physical systems namely G05B 19/418, G05B 19/042, G05B 19/00, G05B 19/18, G06F 19/00, G05B 19/05, G05B 23/02, G05B 11/01, H04L 29/06, and G05B 19/02 (Trappey *et al.*, 2016). We exclude H04L 29/06 which represents the transmission of digital information and G06F 19/00 related to electric digital data processing, since these two patent classes are related to the general transmission and process of data and not only to cyber-physical systems. We also exclude G05B023/02 electric testing or monitoring and G05B011/01 electric control or regulating systems in general, due to the general nature of these patent classes. This leaves us six distinct subclasses of the class G05B control or regulating systems in general; functional elements of such systems; monitoring or testing arrangements for such systems or elements. These six patent classes are described in Table 1.

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Table 1. Industry 4.0 defined in terms of patent classes.

Source: Authors elaboration based on descriptions from WIPO
http://web2.wipo.int/classifications/ipc/ipcpub

IPC	Description
G05B019/042	Program-control systems. Program control other than numerical control, i.e. in sequence controllers or logic controllers using digital processors
G05B019/418	Program-control systems. Total factory control, i.e. centrally controlling a plurality of machines, e.g. direct or distributed numerical control (DNC), flexible manufacturing systems (FMS), integrated manufacturing systems (IMS), computer integrated manufacturing (CIM)
G05B019/05	Program-control systems. Programmable logic controllers, e.g. simulating logic interconnections of signals according to ladder diagrams or function charts
G05B019/18	Program-control systems. Numerical control (NC), i.e. automatically operating machines, in particular machine tools, e.g. in a manufacturing environment, so as to execute positioning, movement or coordinated operations by means of program data in numerical form (G05B 19/418 takes precedence)
G05B019/00	Program-control systems.
G05B019/02	Program-control systems. Electric

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STEP 2. DRAW GROWTH CURVES FOR THE SELECTED PATENT CLASSES

We draw the growth curves in terms of innovative performance, i.e. yearly number of patents, for each of the six patent classes of the industry 4.0 ecosystem in Figure 2.

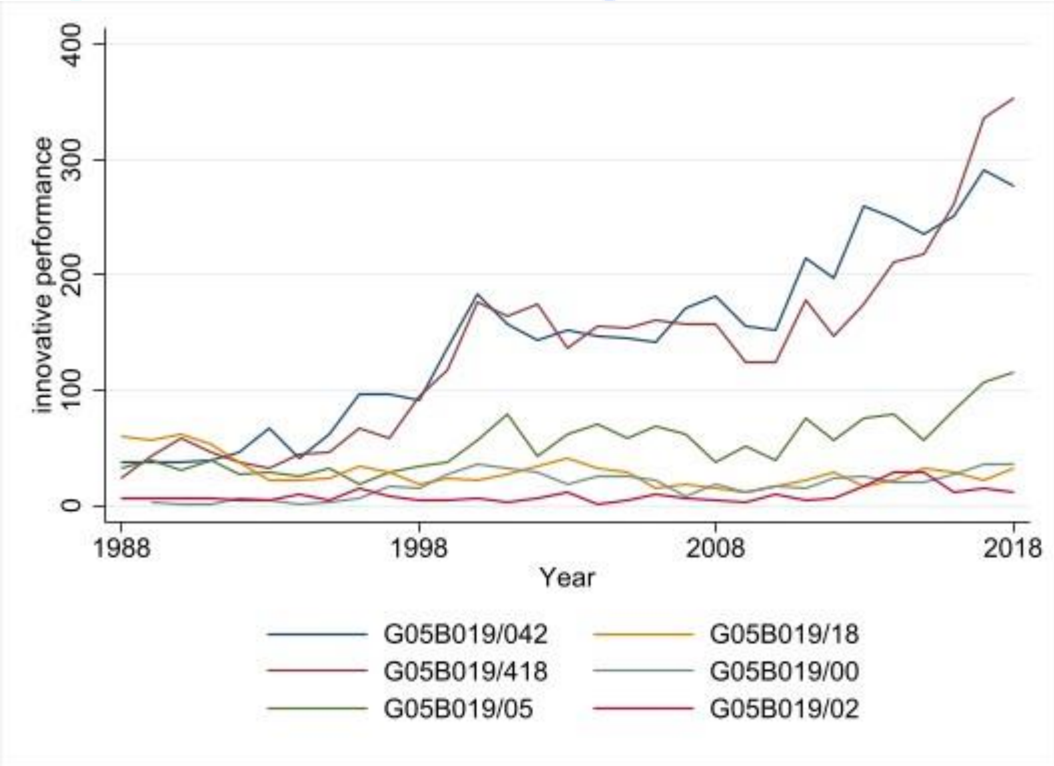

Figure 2. Growth curves for industry 4.0 technologies.

STEP 3. IDENTIFY CORE TECHNOLOGIES IN TERMS OF INNOVATIVE PERFORMANCE AND MATURITY

In Figure 3, the patent classes G05B019/042 and G05B019/418 are notable in terms of innovative performance and growth. We thus identify these two patent classes as core technologies of industry 4.0.

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STEP 4. FIT LOGISTIC GROWTH CURVES TO CORE TECHNOLOGY DATA

We use a nonlinear least-square estimation to fit the following logistic function to the data for each patent class:

$$x = \beta_0 + \frac{\beta_1}{1+e^{-\beta_2(t-\beta_3)}}$$

where x is innovative performance, t is the year, and β is indicated in Table 2. Models 1 and 2 represent the two main patent classes of industry 4.0. For these models, β_0 is taken as 0 and the fitted model is thus a three-parameter function. In Figures 4 and 5, we plot the data together with the fitted logistic function. We see from the adjusted R^2 and the root-mean-square error (RMSE) as well as in the figures that while both patent classes fit the sigmoid curve very well, the fit of model 1 is better and while class G05B019/042 is still in a growth phase, it is nearing stability and convergence. G05B019/418 is experiencing a growth spurt that deviates from the trajectory. This may be a temporary deviation, as has happened before, but it could also indicate a new growth phase for innovation in computer-integrated manufacturing systems of industry 4.0.

Table 2. Logistic function estimates

Model	1		2		3		4	
IPC	G05B019/042		G05B019/418		G06Q010/06		G06Q010/08	
β_1	366.194	**	394.253	**	615.368	**	548.983	**
β_2	0.106	**	0.108	**	0.549	**	0.492	**
β_3	2009.145	**	2009.036	**	2011.371	**	2013.215	**
Model diagnostics								
Adj. R^2	0.983		0.933		0.995		0.996	
RMSE	20.020		36.073		27.356		16.420	
N	75		91		24		34	

** Estimates significant on the 5% level

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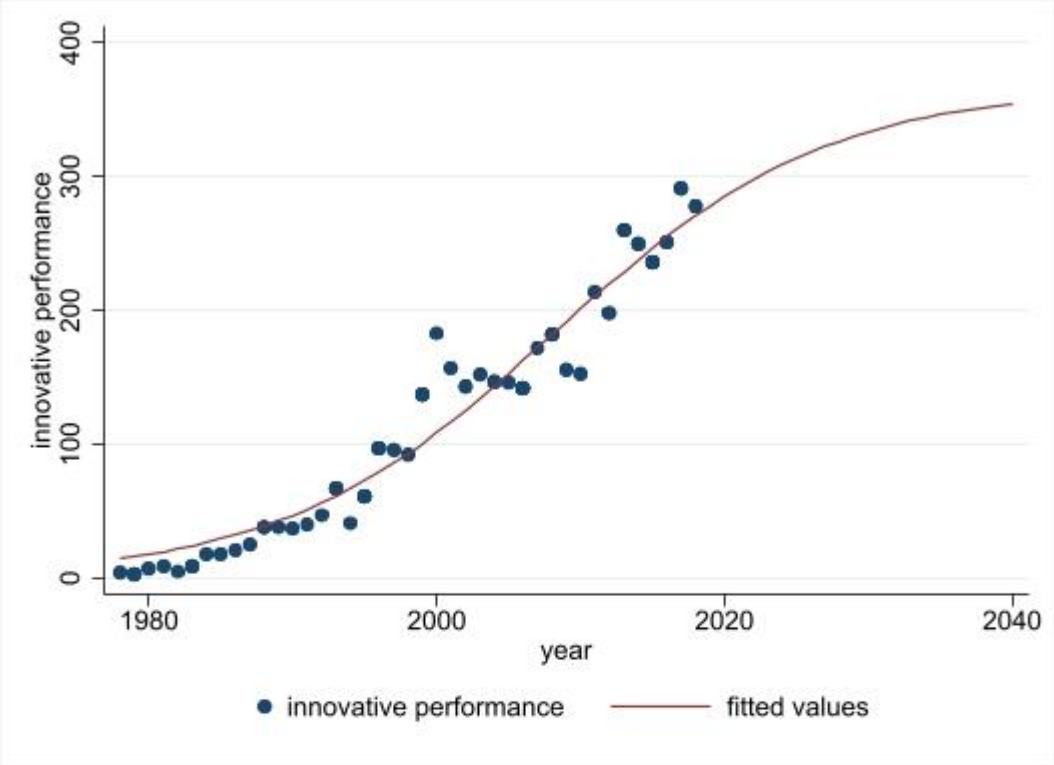

Figure 3. Data for patent class G05B019/042 with fitted sigmoid curve.

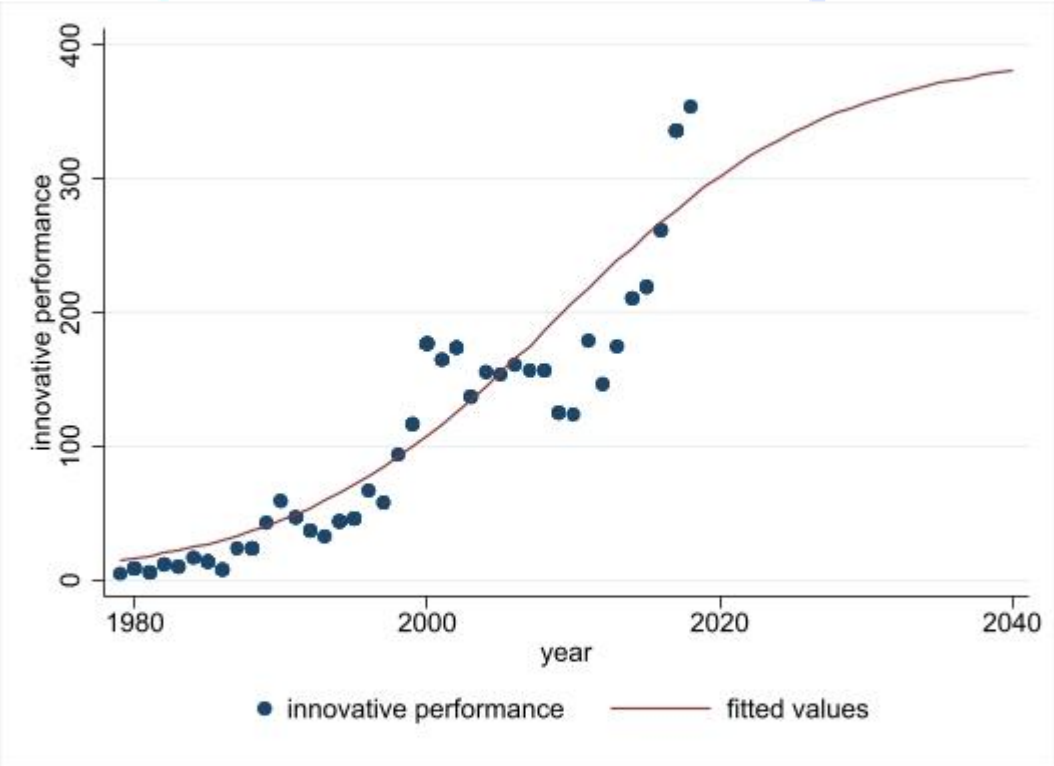

Figure 4. Data for patent class G05B019/418 with fitted sigmoid curve.

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STEP 5. ARE THE CORE TECHNOLOGIES IN THE UPPER STAGE OF THE S-CURVE?

Industry 4.0 has clearly entered a stage of maturity after a stage of rapid growth and is about to reach the upper stage of the sigmoid shape. However, for patent class G05B019/418, the behavior in the last years is unstable.

STEP 6. ANALYZE CITING TECHNOLOGIES

We list those technologies that most frequently cite the core technologies of industry 4.0 in Table 3.

Table 3. Main patent classes citing core technologies of industry 4.0.

Citations to G05B019/042	Percent	Citations to G05B019/418	Percent
G05B019/042	19.91	G05B019/418	12.97
G05B019/05	5.82	G05B019/042	7.12
G05B019/418	4.76	G05B023/02	4.58
G05B023/02	2.65	G05B019/05	2.18
H04L012/28	1.32	G06Q010/00	1.69
G06F009/44	1.06	B25J009/16	1.69
G06F009/445	1.06	H04L029/08	1.62
H04L012/40	1.06	G06Q010/00	1.48
H04L029/06	1.06	G05B019/414	1.13
H04L029/08	0.99	G06F017/50	1.13

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STEP 7. ARE THERE TECHNOLOGIES THAT CITE CORE TECHNOLOGIES BUT DO NOT BELONG TO THE ECOSYSTEM?

Both technologies mostly refer to the own technology, with citations to other technologies being fragmented across a large number of patent classes, and mainly to those within the ecosystem. However, one patent class sticks out in Table 3, for gaining over three percent of citations from patent class G05B019/418 without belonging to the defined ecosystem. This citing class is G06Q010, which represents data processing systems or methods, specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes. The subclass G06Q010/00 refers to systems and methods for administration and management and G06Q010/06 systems resources, workflows, human or project management. Descriptions of the subclasses of G06Q010 are included in Table 4.

Table 4. Subclasses of citing patent class.

Source: Authors elaboration based on descriptions from WIPO http://web2.wipo.int/classifications/ipc/ipcpub

IPC	Description
G06Q010/00	Administration; Management
G06Q010/10	Office automation, e.g. computer aided management of electronic mail or groupware
G06Q010/06	Resources, workflows, human or project management, e.g. organizing, planning, scheduling or allocating time, human or machine resources; Enterprise planning; Organizational models
G06Q010/08	Logistics, e.g. warehousing, loading, distribution or shipping; Inventory or stock management, e.g. order filling, procurement or balancing against orders
G06Q010/04	Forecasting or optimization, e.g. linear programming, "travelling salesman problem" or "cutting stock problem"
G06Q010/02	Reservations, e.g. for tickets, services or events

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REPEAT STEP 2. DRAW GROWTH CURVES FOR THE SELECTED PATENT CLASSES

We draw growth curves for all subclasses of G06Q010 in Figure 5.

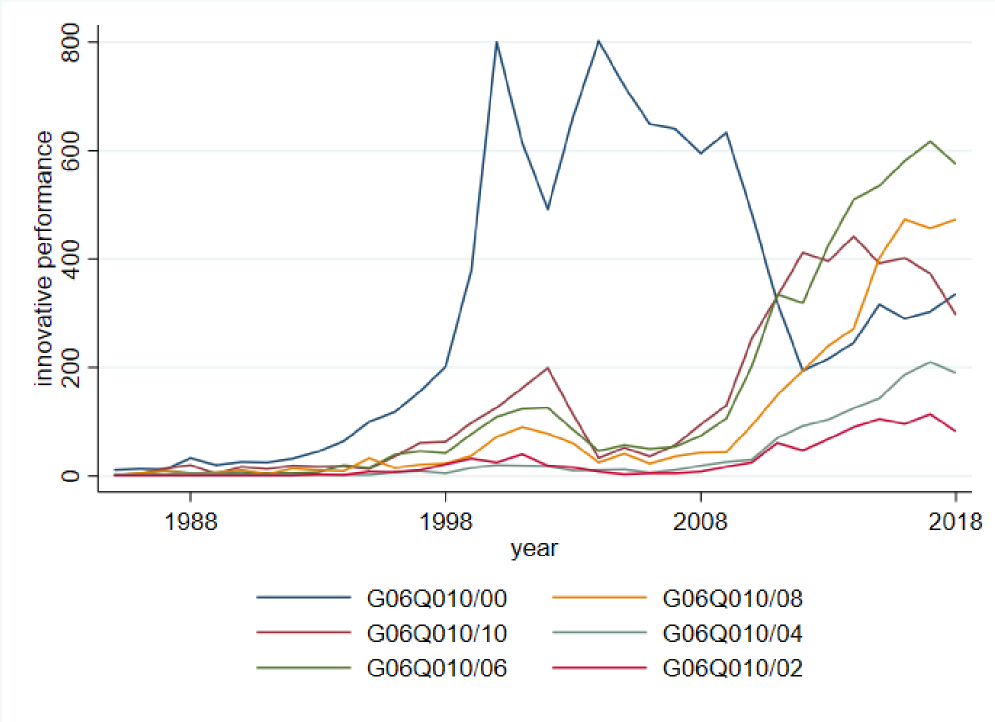

Figure 5. Growth curves for managerial automation.

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REPEAT STEP 3. IDENTIFY CORE TECHNOLOGIES IN TERMS OF INNOVATIVE PERFORMANCE AND MATURITY

We see that the general management and administration systems patent class is giving way to more specific classes, and that two classes exhibit particularly rapid growth, i.e. G06Q010/06 resources, workflows, human or project management and G06Q010/08 logistics. We thus identify the latter two as core technologies.

REPEAT STEP 4. FIT LOGISTIC GROWTH CURVES TO CORE TECHNOLOGY DATA

We again fit the logistic function to the data for patent class G06Q010/06 and G06Q010/08, and display the resulting coefficients and diagnostics in models 3 and 4 of Table 2. We fit the data from year 2006, when these technologies enter a growth cycle.

We plot the data points and the fitted functions in Figures 7 and 8.

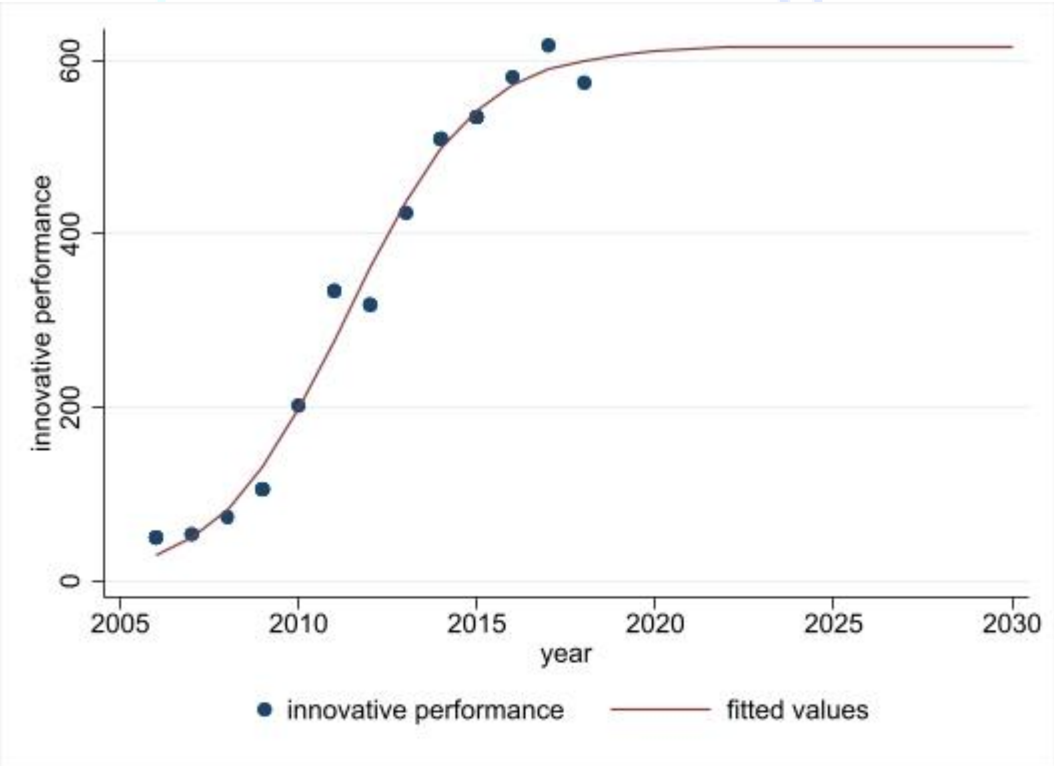

Figure 6. Data for patent class G06Q010/06 with fitted sigmoid curve.

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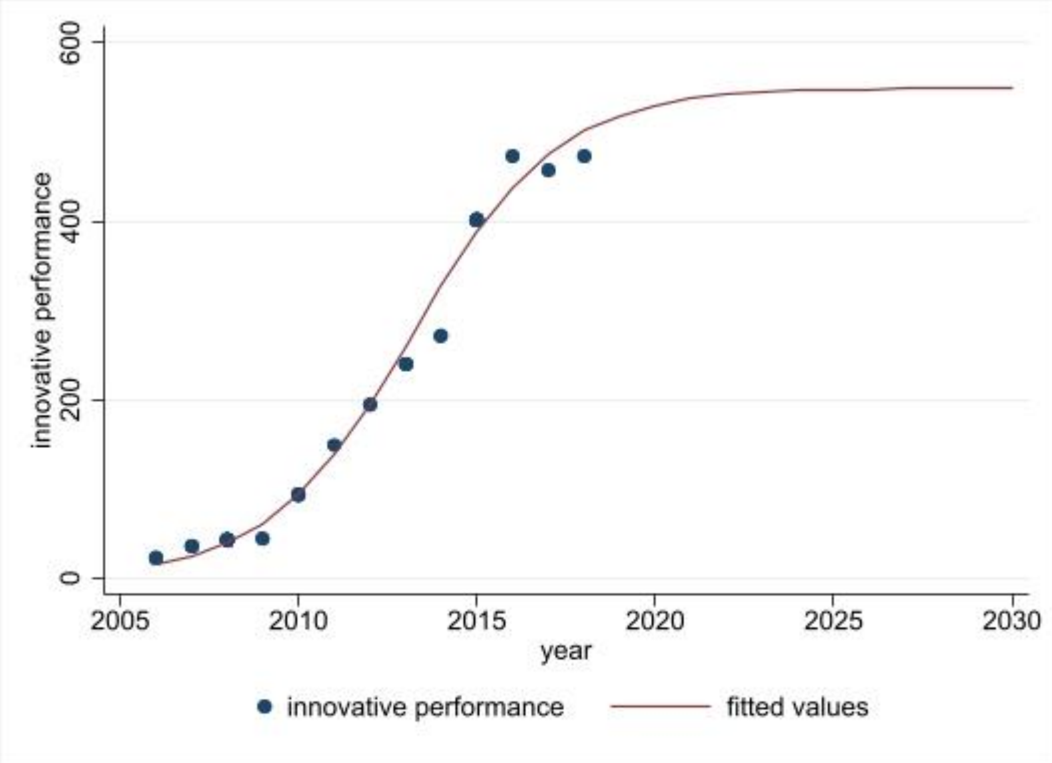

Figure 7. Data for patent class G06Q010/08 with fitted sigmoid curve.

REPEAT STEP 5. ARE THE CORE TECHNOLOGIES IN THE UPPER STAGE OF THE S-CURVE?

The data indicates that the technologies are still in a growth phase although they are nearing the stable upper stage. We thus proceed to the final step by discussing the implications of the validated framework in the following section.

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6. CONCLUSIONS FOR INNOVATION MANAGEMENT

We find that industry 4.0 is in a mature, stable state of development. More importantly, our framework for forecasting enabling technologies permits the identification of subsequent, complementary technologies. This is an important result in the context of technology trajectories. Technologies in such a stable state of development tend to be on a high level of the S-curve (Katz, 1961; Utterback 1994). Hence, it is reasonable to assume that this stability will also lead to a platform for new technological developments, as argued by (Gawer & Cusumano, 2002; 2014). If and how this will lead into a standardization process yielding a dominant design, needs further empirical investigation. Nevertheless, the establishment of an innovation platform is important for the future development of industry 4.0 as a term, and notably, as an innovation concept.

In addition, the framework indicates that we are moving from factory automation to managerial automation. Managerial work is replaced by automation in a wide array of tasks e.g., the management of resources, workflows, people, projects, and office tasks. Managers may progressively find their tasks replaced by automation. Artificial intelligence allows for a redistribution of tasks and with new service-based business models, even smaller firms can implement managerial automation (Ferras-Hernandez et al., 2023). With the right tools, even innovation processes can be originated and facilitated by artificial intelligence (Brem et al., 2023). In the limit, artificial intelligence can guide the strategic management of firms (Ferras-Hernandez et al., 2022).

Frey and Osborne (2017) conclude that managerial tasks requiring a high degree of social intelligence have lower probability of automation. Such managerial tasks which are difficult to automate include discussing issues, resolving problems, and negotiating. Still, the difficulty of automating a certain task does not mean it will not eventually be automated. Apparently, there is a high dependence on the type of task which is performed. Tasks including exploitative behavior are different to tasks related to explorative behavior. In the latter case, a manager has to be open to new things, whereas in an exploitative setup efficiency is the main goal (O'Reilly & Tushman, 2013). An extreme example is an entrepreneur who has to engage in explorative tasks e.g., to develop new products, and exploitative tasks to organize the company with very operational tasks e.g., writing invoices (Brem, 2017). Hence, managerial automation may primarily focus on exploitative tasks, which can be linked to industry 4.0 tools, such as automating the billing process.

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Early work in the 1980's begun discussing the impact of innovation on the automation of human tasks (e.g., Hudson, 1983), or the impact of technological change in organizations (e.g., Damanpour, 1987). However, managerial automation is not substituting industry 4.0 (Schumpeter, 1942), nor it is an extension of these technologies (Adner & Kapoor, 2016). Instead, it is a complementary set of technologies which extends the industry 4.0 ecosystem into a new area previously dominated by humans. The innovation ecosystem perspective thus enables us to identify complementary technologies, and not only substitutions or extensions (Nylund et al., 2022). Complementarities increases the likelihood of discontinuous strategic transformation (Makri et al., 2010).

For managers and policy makers, the framework offers insights regarding the present state and future development of industry 4.0. In Figure 3, we see that the growth phase of innovation in industry 4.0 took place around 2000. The concept became widely implemented around 2011 (Kagermann et al., 2011), and we thus perceive a time lag of about ten years from invention to implementation. If the time lag for managerial automation is similar, that would mean a wide implementation of managerial implementation around 2022-2024. With the shortening time lags of innovation adoption, this lag may be shorter for managerial automation (Brem & Viardot, 2017). The emergence of managerial automation calls for action regarding organizational design, regulation, etc. Since human capital is crucial to industry 4.0 implementation, training in these areas would increase the readiness of firms (Adebanjo et al., 2023). Even simple tools such as chatbots require employee capability (Sharma et al., 2024). Further, the introduced framework for forecasting enabling technologies can be applied by to other innovation ecosystems in order to predict technological change in light of the ever-shortening time cycles.

The simplicity of the proposed method is likely to reduce errors and improve implementation of the resulting predictions, since each step can be understood by the responsible managers (Green & Armstrong, 2015). An inherent limitation in using patent data is that it focuses on the invention process rather than on innovation diffusion. To deepen the understanding of the development of the industry 4.0 innovation ecosystem, future research may add complementary data on functions related to diffusion. The lack of data for the last few years also constitutes a limitation of this article. Repeating the analysis as new data becomes available is likely to yield additional insights. The use of European data only ensures consistency within the data set, but inclusion of data from other continents would open avenues for research regarding the globalization of industry 4.0.

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With new tools for detecting enabling technologies, researchers, managers, and policy makers can prepare to adapt to technological change and to contribute to the development of innovation ecosystems. Hence, there is much future research to be done with these powerful tools.

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7. REFERENCES

Adebanjo, D., Laosirihongthong, T., Samaranayake, P., & Teh, P. L. (2023). Key enablers of industry 4.0 development at firm level: Findings from an emerging economy. *IEEE Transactions on Engineering Management, 70*(2), 400-416.

Adner, R., & Kapoor, R. (2016). Innovation ecosystems and the pace of substitution: Re-examining technology S-curves. *Strategic Management Journal, 37*(4), 625-648.

Ahuja, G., & Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: a longitudinal study. *Strategic Management Journal, 22*(3), 197-220.

Alcácer, V., & Cruz-Machado, V. (2019). Scanning the Industry 4.0: A Literature Review on Technologies for Manufacturing Systems. *Engineering Science and Technology, an International Journal, 22*(3), 899–919.

Ansoff, H. I. (1975). Managing strategic surprise by response to weak signals. *California Management Review, 18*(2), 21-33.

Armstrong, J. S., Green, K. C., & Graefe, A. (2015). Golden rule of forecasting: Be conservative. *Journal of Business Research, 68*(8), 1717-1731.

Autio, E., & Thomas, L. D. W. (2014). Innovation Ecosystems: Implications for Innovation Management. In M. Dodgson, D. M. Gann, & N. Phillips (Eds.), *The Oxford Handbook of Innovation Management*. Oxford University Press.

Baldwin, C. Y., Bogers, M. L., Kapoor, R., & West, J. (2024). Focusing the ecosystem lens on innovation studies. *Research Policy*, *53*(3), 104949.

Basalla, G. (1988). *The Evolution of Technology*. Cambridge University Press.

Bendel, O. (2017). Stichwort: Industrie 4.0. In *Gabler Wirtschaftslexikon*. Springer Gabler.

Benitez, G. B., Ayala, N. F., & Frank, A. G. (2020). Industry 4.0 innovation ecosystems: An evolutionary perspective on value cocreation. *International Journal of Production Economics, 228*, 107735.

Bereznoy, A., Meissner, D., & Scuotto, V. (2021). The intertwining of knowledge sharing and creation in the digital platform-based ecosystem. A conceptual study on the lens of the open innovation approach. *Journal of Knowledge Management, 25*(8), 2022-2042.

Bigliardi, B., Bottani, E., & Casella, G. (2020). Enabling technologies, application areas and impact of Industry 4.0: A bibliographic analysis. *Procedia Manufacturing, B(2019), 322–326.

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Bodkhe, U., Tanwar, S., Parekh, K., & Khanpara, P. (2020). Blockchain for Industry 4.0: A Comprehensive Review. *IEEE Access, 8,* 79764-79800.

Brem, A. (2017). Creativity and routine: Conceptual considerations on managing organizational ambidexterity in entrepreneurial ventures. *International Journal of Entrepreneurship and Innovation Management, 21*(3), 261-273.

Brem, A., Giones, F., & Werle, M. (2023). The AI digital revolution in innovation: A conceptual framework of artificial intelligence technologies for the management of innovation. *IEEE Transactions on Engineering Management*, 70(2), 770-776.

Brem, A., & Nylund, P. A. (2024). The inertia of dominant designs in technological innovation: an ecosystem view of standardization. *IEEE Transactions on Engineering Management*, 71, 2640-2648

Brem, A., Nylund, P. A., & Schuster, G. (2016). Innovation and de facto standardization: The influence of dominant design on innovative performance, radical innovation, and process innovation. *Technovation*, 50, 79-88.

Brem, A., & Viardot, E. (2017). Revolution of innovation management: The digital breakthrough. In A. Brem & E. Viardot (Eds.), *Revolution of Innovation Management*. Palgrave Macmillan: London.

Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies 'Engines of growth?' *Journal of Econometrics*, 65(1), 83-108.

Brettel, M., Friederichsen, N., Keller, M., & Rosenberg, M. (2014). How virtualization, decentralization and network building change the manufacturing landscape: An industry 4.0 perspective. *International Journal of Mechanical, Industrial Science and Engineering*, 8(1), 37-44.

Carignani, G., Cattani, G., & Zaina, G. (2019). Evolutionary chimeras: A Woesian perspective of radical innovation. *Industrial and Corporate Change*, 28(3), 511-528.

Choi, C., & Park, Y. (2009). Monitoring the organic structure of technology based on the patent development paths. *Technological Forecasting and Social Change*, 76(6), 754-768.

Dąbrowska, J., Almpanopoulou, A., Brem, A., Chesbrough, H., Cucino, V., Di Minin, A., Giones, F., Hakala, H., Marullo, C., Mention, A.-L., Mortara, L., Nørskov, S., Nylund, P. A., Oddo, C. M., Radziwon, A., and Ritala, P. 2022. Digital transformation, for better or worse: a critical multi-level research agenda. R&D Management 52(5): 930–954.

Damanpour, F. (1987). The adoption of technological, administrative, and ancillary innovations: Impact of organizational factors. *Journal of Management*, 13(4), 675-688.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 956745. Results reflect the author's view only. The European Commission is not responsible for any use that may be made of the information it contains.

Dattée, B., Alexy, O., & Autio, E. (2018). Maneuvering in poor visibility: How firms play the ecosystem game when uncertainty is high. *Academy of Management Journal*, 61(2), 466-498.

Daymond, J., Knight, E., Rumyantseva, M., & Maguire, S. (2022). Managing ecosystem emergence and evolution: Strategies for ecosystem architects. *Strategic Management Journal*, 44(4), O1-O27.

Denicolai, S., Zucchella, A., & Magnani, G. (2021). Internationalization, digitalization, and sustainability: Are SMEs ready? A survey on synergies and substituting effects among growth paths. *Technological Forecasting and Social Change*, 166, 120650.

Dosi, G. (1982). Technological paradigms and technological trajectories. *Research Policy*, 11, 147-162.

Dunlap, D., McDonough III, E. F., Mudambi, R., & Swift, T. (2016). Making up is hard to do: knowledge acquisition strategies and the nature of new product innovation. *Journal of Product Innovation Management*, 33(4), 472-491.

Feldman, M. P., & Yoon, J. W. (2012). An empirical test for general-purpose technology: An examination of the Cohen–Boyer rDNA technology. *Industrial and Corporate Change, 21*(2), 249-275.

Ferras-Hernandez, X., Nylund, P. A., & Brem, A. (2023). The emergence of dominant designs in artificial intelligence. *California Management Review, 65*(3), 73–91.

Ferras-Hernandez, X., Nylund, P. A., & Brem, A. (2022). Strategy Follows the Structure of Artificial Intelligence. *IEEE Engineering Management Review, 50*(3), 17-19.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254-280.

Gawer, A., & Cusumano, M. A. (2002). Platform leadership: How Intel, Microsoft, and Cisco drive industry innovation. Harvard Business School Press: Boston, MA.

Gawer, A., & Cusumano, M. A. (2014). Industry platforms and ecosystem innovation. *Journal of Product Innovation Management, 31*(3), 417–433.

Geerts, A., Leten, B., Belderbos, R., & Van Looy, B. (2018). Does spatial ambidexterity pay off? On the benefits of geographic proximity between technology exploitation and exploration. *Journal of Product Innovation Management, 35*(2), 151-163.

Ghobakhloo, M. (2018). The future of manufacturing industry: A strategic roadmap toward Industry 4.0. *Journal of Manufacturing Technology Management, 29*(6), 910–936.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 956745. Results reflect the author's view only. The European Commission is not responsible for any use that may be made of the information it contains.

Granstrand, O., & Holgersson, M. (2020). Innovation ecosystems: A conceptual review and a new definition. *Technovation, 90*, 102098.

Green, K. C., & Armstrong, J. S. (2015). Simple versus complex forecasting: The evidence. *Journal of Business Research, 68*(8), 1678-1685.

Ivanov, D., Tang, C. S., Dolgui, A., Battini, D., & Das, A. (2021). Researchers' perspectives on Industry 4.0: Multi-disciplinary analysis and opportunities for operations management. *International Journal of Production Research, 59*(7), 2055-2078.

Hall, B. H., & Ziedonis, R. H. (2001). The patent paradox revisited: An empirical study of patenting in the U.S. semiconductor industry, 1979–1995. *Rand Journal of Economics, 32*, 101-128.

Haessler, P., Giones, F., & Brem, A. (2023). The who and how of commercializing emerging technologies: A technology-focused review. *Technovation*, *121*, 102637.

Henderson, R., & Clark, K. B. (1990). Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly, 35*(1), 9-30.

Hermann, M., Pentek, T., & Otto, B. (2015). Design principles for Industrie 4.0 scenarios: A literature review. *Working Paper No. 01 / 2015, Technical University of Dortmund: Dortmund*.

Holroyd, C. (2022). Technological innovation and building a 'super smart' society: Japan's vision of society 5.0. *Journal of Asian Public Policy, 15*(1), 18.

Howard, M. D., Boeker, W., & Andrus, J. L. (2019). The spawning of ecosystems: how cohort effects benefit new ventures. *Academy of Management Journal, 62*(4), 1163-1193.

Huang, H. C., & Su, H. N. (2019). The innovative fulcrums of technological interdisciplinarity: An analysis of technology fields in patents. *Technovation, 84-85*, 59-70.

Hudson, J. D. (1983). Office technology: Turning promises into gains. *Global Business and Organizational Excellence, 2*(3), 257-265.

Huenteler, J., Ossenbrink, J., Schmidt, T. S., & Hoffmann, V. H. (2016). How a product's design hierarchy shapes the evolution of technological knowledge—Evidence from patent-citation networks in wind power. *Research Policy, 45*(6), 1195-1217.

Jacobides, M. G., Cennamo, C., & Gawer, A. (2018). Towards a theory of ecosystems. *Strategic Management Journal, 39*(8), 2255–2276.

Jaffe, A., & Lerner, J. (2004). Innovation and its discontents: how our broken patent system is endangering innovation and progress, and what to do about it. Princeton University Press: Princeton.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 956745. Results reflect the author's view only. The European Commission is not responsible for any use that may be made of the information it contains.

Kagermann, H., Lukas, W. D., & Wahlster, W. (2011). Industrie 4.0: Mit dem Internet der Dinge auf dem Weg zur 4. industriellen Revolution. *VDI Nachrichten, 13*, 2.

Kagermann, H., Wahlster, W., & Helbig, J. (2013). Securing the future of German manufacturing industry: Recommendations for implementing the strategic initiative industrie 4.0. Industry-Science Research Alliance: Frankfurt am Main.

Katz, E. (1961). The social itinerary of technical change: two studies on the diffusion of innovation. *Human Organization, 20*(2), 70-82.

Keil, T., Maula, M., Schildt, H., & Zahra, S. A. (2008). The effect of governance modes and relatedness of external business development activities on innovative performance. *Strategic Management Journal, 29*, 895-907.

Kumar, V., Lai, K. K., Chang, Y. H., Bhatt, P. C., & Su, F. P. (2021). A structural analysis approach to identify technology innovation and evolution path: a case of m-payment technology ecosystem. *Journal of Knowledge Management, 25*(2), 477-499.

Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manufacturing Letters, 3*, 18-23.

Lenz, R. C. (1985). Rates of adoption/substitution in technological change. Technology Futures, Inc: Austin, TX.

Levinthal, D. A. (1998). The slow pace of rapid technological change: gradualism and punctuation in technological change. *Industrial and Corporate Change, 7*(2), 217-247.

Li, L. (2018). China's manufacturing locus in 2025: With a comparison of "Made-in-China 2025" and "Industry 4.0." *Technological Forecasting and Social Change*, *135*(February), 66–74.

Lipsey, R. G., Bekar, C., & Carlaw, K. (1998). What requires explanation? In E. Helpman (Ed.), *General Purpose Technologies and Economic Growth* (pp. 1–31). MIT Press.

Michel, J., & Bettels, B. (2001). Patent citation analysis—a closer look at the basic input data from patent search reports. *Scientometrics*, *51*, 185-201.

Maier, M. A., Korbel, J. J., & Brem, A. (2015). Innovation in supply chains – solving the agency dilemma in supply networks by using industry 4.0 technologies. *International Journal of Communication Networks and Distributed Systems*, *15*(2/3), 235–247.

Makri, M., Hitt, M. A., & Lane, P. J. (2010). Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions. *Strategic Management Journal*, *31*(6), 602-628.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 956745. Results reflect the author's view only. The European Commission is not responsible for any use that may be made of the information it contains.

Matzler, K., Veider, V., Hautz, J., & Stadler, C. (2015). The impact of family ownership, management, and governance on innovation. *Journal of Product Innovation Management*, *32*(3), 319-333.

Miller, C. D., & Toh, P. K. (2022). Complementary components and returns from coordination within ecosystems via standard setting. *Strategic Management Journal*, *43*(3), 627–662.

Mueller, J. M., Buliga, O., & Voigt, K.-I. (2018). Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0. *Technological Forecasting and Social Change*, *132*, 2–17.

Najmaei, A., & Sadeghinejad, Z. (2023). Green and sustainable business models: historical roots, growth trajectory, conceptual architecture and an agenda for future research—A bibliometric review of green and sustainable business models. *Scientometrics*, *128*(2), 957-999.

No, H. J., & Park, Y. (2010). Trajectory patterns of technology fusion: Trend analysis and taxonomical grouping in nanobiotechnology. *Technological Forecasting and Social Change*, *77*(1), 63-75.

Nylund, P. A., Brem, A., & Agarwal, N. (2022). Enabling technologies mitigating climate change: The role of dominant designs in environmental innovation ecosystems. *Technovation*, *117*, 102271.

Nylund, P. A., Brem, A., Chaudhary, P., & D'Alberti, F. (2024). The impact of crisis on interecosystemic innovation: dynamics of Enel's hydrogen ecosystem. *International Journal of Innovation Management*, 2450006.

Nylund, P. A., Ferràs-Hernández, X., Pareras, L., & Brem, A. (2022). The emergence of entrepreneurial ecosystems based on enabling technologies: Evidence from synthetic biology. *Journal of Business Research*, *149*, 728-735.

O'Reilly, C. A., & Tushman, M. L. (2013). Organizational ambidexterity: Past, present, and future. *Academy of Management Perspectives*, *27*(4), 324-338.

Oztemel, E., & Gursev, S. (2020). Literature review of Industry 4.0 and related technologies. *Journal of Intelligent Manufacturing*, 31(1), 127–182.

Pearl, R. (1925). *The Biology of Population Growth*. A. Knopf: New York.

Pereira, A. C., & Romero, F. (2017). A review of the meanings and the implications of the Industry 4.0 concept. *Procedia Manufacturing*, 13, 1206–1214.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 956745. Results reflect the author's view only. The European Commission is not responsible for any use that may be made of the information it contains.

Porter, A. L. (1991). *Forecasting and Management of Technology* (Vol. 18). John Wiley and Sons: Hoboken, NJ.

Quillen, C., & Webster, O. (2001). Continuing patent applications and performance of the US patent office. *Federal Circuit Bar Journal*, 11, 1-21.

Rajkumar, R., Lee, I., Sha, L., & Stankovic, J. (2010). Cyber-physical systems. In S. Sapatnekar (Ed.), *Proceedings of the 47th Design Automation Conference*.

Rowe, G., & Wright, G. (1999). The Delphi technique as a forecasting tool: Issues and analysis. *International Journal of Forecasting*, 15(4), 353-175.

Rusek, K., Kleszcz, A., & Cabellos-Aparicio, A. (2023). Bayesian inference of spatial and temporal relations in AI patents for EU countries. *Scientometrics*, 128(6), 3313-3335.

Schumpeter, J. A. (1942). *Capitalism, socialism and democracy*. Unwin University Books: London.

Sharma, S., Singh, G., Islam, N., & Dhir, A. (2024). Why Do SMEs Adopt Artificial Intelligence-Based Chatbots? *IEEE Transactions on Engineering Management*, 71, 1773-1786,

Stuart, T. E. (1999). A structural perspective on organizational innovation. *Industrial and Corporate Change*, 8(4), 745-775.

Stuart, T. E. (2000). Interorganizational alliances and the performance of firms: a study of growth and innovation rates in a high-technology industry. *Strategic Management Journal*, 21, 791–811.

Szalavetz, A. (2019). Industry 4.0 and capability development in manufacturing subsidiaries. *Technological Forecasting and Social Change*, 145, 384-395.

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.

Trajtenberg, M. (1990). A penny for your quotes: patent citations and the value of innovations. *The Rand Journal of Economics*, 21(1), 172-187.

Trappey, A. J., Trappey, C. V., Govindarajan, U. H., Sun, J. J., & Chuang, A. C. (2016). A review of technology standards and patent portfolios for enabling cyber-physical systems in advanced manufacturing. *IEEE Access*, 4, 7356-7382.

Utterback, J. M. (1994). *Mastering the dynamics of innovation: how companies can seize opportunities in the face of technological change*. Harvard Business School Press: Boston, MA.

Van Pottelsberghe de la Potterie, B., & François, D. (2009). The cost factor in patent systems. *Journal of Industry, Competition and Trade*, 9(4), 329-355.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 956745. Results reflect the author's view only. The European Commission is not responsible for any use that may be made of the information it contains.

Wareham, J., Fox, P. B., & Cano Giner, J. L. (2014). Technology ecosystem governance. *Organization Science*, 25(4), 1195-1215.

Webb, C., Dernis, H., Harhoff, D., & Hoisl, K. (2005). Analysing European and international patent citations: a set of EPO patent database building blocks. *STI Working Paper 2005/09*. OECD: Paris.

Xu, L. D., Xu, E. L., & Li, L. (2018). Industry 4.0: State of the art and future trends. *International Journal of Production Research*, 56(8), 2941–2962.

Yang, J., Chesbrough, H., & Hurmelinna-Laukkanen, P. (2022). How to appropriate value from general-purpose technology by applying open innovation. *California Management Review*, 64(3), 24–48.

Yu, D., & Yan, Z. (2022). Combining machine learning and main path analysis to identify research front: from the perspective of science-technology linkage. *Scientometrics*, *127*(7), 4251-4274.

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