A Framework for Investigating the Adoption of Key Technologies: Presentation of the Methodology and Explorative Analysis of Emerging Practices

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***Abstract*—In this article, we present a framework for performing a systematic literature review on the implementation of emerging business practices and the adoption of these key technologies: three-dimensional printing, artificial intelligence, blockchain, computing, digital applications, geospatial technologies, immersive environments, Internet of things, open and crowd-based platforms, proximity technologies, and robotics. Through the content analysis of the full text of scientific papers, emerging practices are captured and then classified within a group of standardized labels. This allows to summarize an emerging practice as the use of a key technology within a business context—represented by industry, business function, and business process adopting the technology—with the aim of achieving improvements in terms of business performance. The adoption of this methodology allows the recognition of the opportunities for companies of enhancing performance through key technologies. With this study, the framework is tested by classifying more than 22 000 scientific articles and extracting 15 708 emerging practices. The explicative power of data collected is demonstrated by performing an explorative analysis aiming at illustrating the state-of-the-art of emerging practices. Moreover, by employing association rules algorithms, 262 practices are found as the most frequent and relevant and are the candidate for becoming future best practices.**

***Index Terms*—Artificial intelligence (AI), blockchain, emerging practices, Industry 4.0, Internet of Things (IoT), key technologies, robotics, systematic literature review, 3-D printing.**

I. Introduction

THE fourth industrial revolution, also referred to as Industry 4.0, focused the attention of policymakers, researchers, practitioners, industry analysts, and managers on the employment of key technologies to support future investments, consumption, growth, employment, and trade [1], [2]. Despite the initial reference to the manufacturing industry and the concept of smart factory [3], [4], the implications of Industry 4.0 also regard other sectors where technologies can be a driver of business performance improvement [5], [6], [7]. Within the industry 4.0 paradigm, the appropriate implementation of key technologies is fundamental to achieve positive outcomes [8]. Such technologies can be considered as either "new" since they are featured by radical novelty, with promising but uncertain impacts [1] or "cutting edge" because they employ the most current and high-level developments. Therefore, companies can rely on these technologies to carry out new emerging business practices, which depart from traditional and current best practices, in order to achieve significant competitive advantage. However, since the improvements of business performance determined by the adoption of emerging practices are unproven and not easily repeatable, companies investing in such technologies have to accept the risks of failure [9]. Thus, many companies are reluctant to change since emerging practices only promise to solve business problems [10]. Indeed, they prefer to use standard or best practices employing consolidated technologies that have proven a positive impact on the business, with a limited risk.

Scientific literature supports companies, providing examples of application, even though the scientific debate is often oriented on technical challenges rather than the organizational ones [11], [12], [13]. For instance, the literature on blockchain has particularly stressed technical issues, but its real impact on the business is still questionable and under investigation [13], [14]. Anyway, the literature anticipates emerging trends in technology management [15] and provides significant suggestions to companies. Because of the wide number of scientific papers facing the issues of emerging practices, the research is fragmented in thousands of contributions, and it is difficult to understand the current state-of-the-art. The purpose of this work is to present a framework for performing a systematic literature review on the state-of-the-art of emerging practices so that researchers can monitor the advancements in terms of implementation of key technologies, and companies can understand which applications have been sufficiently tested and can be considered worthy of consideration. Such a framework supports the building of a repository of emerging practices employing key technologies based on the standardization of the emerging practices captured by content analysis of scientific papers' full texts. Indeed, scientific literature anticipates future business implementations so that, by examining the repository, it is possible to forecast the future role of technologies [15], [16]. Each emerging practice is summarized as the adoption of a key technology within a specific business context, with implications in terms of enhancement of the business performance. It is important to define the business impact because companies can have a clear understanding of the potential effects that will derive from the implementation of key technology. This reduces the uncertainty and the risks associated with the adoption of emerging practices since the positive effects on business performance can be evaluated on real case studies and projects from which the practice is extracted.

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At the end of July 2022, more than 22 000 scientific papers published from 2019 to 2022 were studied and 15 708 practices recorded within the repository. Data within the repository were recorded by a team of researchers in the field of organization, engineering, and technology management. In particular, by following an inductive approach [17], [18], 11 categories of key technologies are defined: *3-D printing, artificial intelligence (AI), blockchain, computing, digital applications, geospatial technologies, immersive environments, Internet of Things (IoT), open and crowd-based platforms, proximity technologies, and robotics*.

In the literature, no other literature review covers such a large set of key technologies and no study based on thousands of scientific papers was found. Consequently, in addition to practical and managerial usefulness of the framework, from the analysis of the repository, many interesting insights emerge for scholars. Each emerging practice has different opportunities of implementation and peculiarities in terms of impacts on business performance, industry, business function, and business process where it can be carried out. To show the explicative power of the framework, this article will present an explorative analysis of the repository in order to answer the following research question.

> *Which are the most frequent and relevant emerging practices that could become future best practices?*

Indeed, emerging practices are analyzed by implementing association rule mining techniques in order to understand for each key technology, which are the emerging practices that are likely to become the future best practices, since they are both most frequently proposed in case studies and with higher rates of stability in terms of the type of impact on the business performance that are able to achieve.

The rest of this article is organized as follows. An overview is presented of the concepts of key technologies and emerging practices to underscore the usefulness of detecting novel trends for achieving competitive advantage and the classification of key technologies to put in evidence the limitations of current literature. Indeed, with this work, 87 key technologies are considered, grouped in 11 macrocategories. Furthermore, the framework is presented. Indeed, to improve the quality of the systematic literature review, from the content analysis of scientific papers, a combination of the standardized variables and labels is determined so that it is possible to build a database of key technologies from scientific papers. Indeed, the analysis and interpretation of scientific papers was devoted to converting information into the standardized fields of the repository, as discussed in the section. These variables are linked to key technologies, business context, and impact on business performance. As to key technologies, a focus on the taxonomy of 11 key technologies, derived from a significant classification activity, is presented. Furthermore, the other variables—industry, business function, business process, and impacts—are introduced, and information about data collection from scientific papers is reported. Then, results of the analysis of the repository are described with a first descriptive analysis of each variable and a subsequent exploration of the most frequent and relevant combinations of variables that can be considered as the basis of potential future best practices for businesses. Such an analysis is performed by employing association rules techniques, which are machine learning algorithms that are able to find patterns and capture significant relationships among variables. Discussion will underscore theoretical contributions, methodological issues, and practical/managerial implications. Finally, conclusions will close the work.

II. Theoretical Background

A. Key Technologies and Business Practices

According to the supply-chain operations reference (SCOR) model, a business practice is "a unique way to configure a process or a set of processes," using particular technologies, skills, sequences, or methods. Three types of practices are widely acknowledged: standard, best, and emerging. Standard practices are the default practices that companies use to do business that do not provide any competitive advantage or significant cost saving and are associated with low risks and results [19]. Best practices are the best current repeatable and structured practices that have a proven positive impact on the business, with moderate risk and results [20]. Emerging practices employ new technologies or knowledge and differ in the way of organizing processes. Compared with best practices, they are unproven and not easily repeatable; therefore, they are associated with high risks [21]. However, if correctly and opportunely implemented, they could provide a particular competitive advantage. Therefore, when firms plan to implement emerging practices, they decide to accept the risk of failure, hoping to achieve a significant performance improvement [20]. Early adoption could lead to significant rewards but accepting the risk of failure. In line with the industry 4.0 perspective, the use of key technologies within emerging practices is more and more frequent [22]. Key technologies assume a fundamental role because they can "unlock" new practical applications where they are employed to achieve relevant results in terms of outcome, e.g., organizational or market performance [23]. Practices employing key technologies cannot be considered best practices since new technologies are potential breakthroughs that can only promise to solve business problems, but it is necessary to prove their real usefulness.

Recently, scientific research has focused the attention on the adoption of key technologies to improve, convert, and renew traditional practices. The Industry 4.0 paradigm, based on enhancing productivity through digitalization, automation, and connectivity with the progress of key technologies, is expected to affect many aspects of society and industry [24]. This new concept is based on cyber–physical systems in which there is an integration of both virtual and physical participants. The purpose of this paradigm is to effectively control systems in real time by exploiting the Internet and other new technologies [25]. This industrial vision is considered the right solution for solving problems, such as accelerating innovation cycles, increasing demand volatility, and increasing product personalization [26]. In particular, the implementation of key technologies will allow industries to increase production where necessary through the modularity and flexibility of production systems [27].

Key technologies go through several stages before their general acceptance and adoption by society. Various standard adoption models have recently been proposed to help predicting the diffusion of key technologies by providing a structured perspective on the degree of maturity of a key technology, through different stages [28]. Among such adoption models, the Gartner Hype Cycle takes into account two elements—hype level and business maturity—and classifies a technology lifecycle into five stages: technology trigger, peak of inflated expectations, through of disillusionment, slope of enlightenment, and plateau of productivity. Then, technologies are also associated with three additional elements: the maturity level, the time to plateau, and the market penetration [29]. As a recent example, blockchain technology had a period of initial excitement in 2016, reached the peak of inflated expectations around 2018, and entered the trough of disillusionment stage at the end of 2019 [30]. In addition to the Gartner curve, the literature suggested various standard curves to portray the evolution of technology over time, such as the "S-shaped" or logistics performance curve, showing the cumulative performance growth for a technology [31], [32]. In addition, in the literature, there are technology adoption curves that show the speed of technology adoption by both consumers and companies [33]. According to this approach, the adoption rate is classified into five different categories: innovators, early adopters, early majority, late majority, and laggards [34]. Among these categories, early adopters can be described as visionaries because they are the most willing to invest time and resources in technological innovation in order to test and validate the technologies in their business processes [35], [36]. In this way, early adopters motivate other companies to invest in certain key technologies to bridge the competitive gap [37]. The adoption of key technologies is considered important for companies because it allows them to obtain competitive advantage for two reasons: to support business processes in order to reduce costs and to save time by improving production yields [9]. However, adopting a key technology is difficult, and it is not always possible to predict its diffusion using these adoption models. On the one hand, firms could carry out an aggressive strategy and early implement the technology to maximize the returns from being early adopter. From the other hand, conservative strategies could suggest minimizing risks by adopting innovation later, when a wider number of positive cases of implementation have been recognized. For this reason, it is important to assess key technologies and their trends early on, as they may have an impact on future practices that could change businesses.

Still, it is difficult to understand which emerging practices that implement key technologies will be the future best practices widely accepted by companies. This work provides a methodology to monitor the state-of-the-art of the implementation of key technologies in business contexts so that it is possible to find which applications have the highest potential for becoming best practices in the future. To contextualize the areas of adoption, the methodology suggests a taxonomy for technologies, industries, business functions, business processes, and impacts so that the most interesting applications can be identified by the combination of these elements. The proposed framework aims to guide companies toward the adoption of emerging practices through the application of specific key technologies in line with the perspective of industry 4.0. The novelty of the article is to outline a map of key technologies that industrialists, managers, and other actors could take into account to improve business functions and business performance. In this way, stakeholders can consider the implementation of emerging practices to make decisions with greater awareness regarding the possible achievable results.

B. Classification of Key Technologies

In the literature, there are several works that classify and investigate key technologies in different areas [4], [8]. Scientific research is predominantly focused on the analysis of single technologies and discussion of single areas of application. For example, Rolandi et al. [6] classified key technologies for the agriculture sector to assess their possible impacts, while Gkoumas and Tsakalidis [38] evaluated the usefulness of key technologies in the transportation sector.

Several researchers evaluated and classified the technologies in specific areas. For example, Ponis et al. [39] analyzed the influence of key technologies in the perspective of the circular economy. Nti et al. [40] examined the impacts that these technologies can have on engineering processes. Other authors investigated the positive and negative effects on business that digital technologies can generate within supply chains [41], [42]. Many studies classify the implementation of the technologies in the industrial environment and try to identify the challenges and benefits [43]. Others evaluated how the new technologies transform and improve operations management practices [44], [45]. Even though there is a plethora of studies that classify and investigate key technologies, the originality of this work consists in deeply exploring the impacts of various technologies in different business contexts and analyzing the multiple practices that could be developed by companies. This research aims at investigating the implementation of key technologies in all contexts, departing from the current literature. As shown in Table I, studies in the literature are limited to only some areas, such as single sectors or specific technologies. In consideration of the aim of this research, it is necessary to take into account thousands of scientific articles. The current literature considers only a few practices at a time and there is not a formal purpose to present a standardized taxonomy of key technologies. For example, many articles are focused on a specific area, such as supply-chain management (SCM), Industry 4.0, or the manufacturing industry. Moreover, the classification of key technologies is not derived from a deep investigation. Finally, the number of analyzed articles and the identified practices are much lower than in this work. This depends on the different purpose of this research, but it can be considered as an additional contribution since the wider range of analyzed articles guarantees higher robustness to the suggested taxonomy.

Extending the comparison to review papers, the literature is featured by several works that analyze a significant number of articles; however, their final purpose is to provide an overview of the current state-of-the-art of scientific research without identifying the emerging practices that are worthy of implementation [49], [50]. The suggested framework differs from the others in the literature since it allows the analysis with different perspectives. First, the classification of technologies, impacts, industries, business functions, and processes derives from a literature review of thousands of scientific articles and has been constantly updated and reviewed during the data collection. Second, this research aims at identifying the links among emerging practices, impacts, key technologies, business functions, business processes, and industries in a formal way. Hence, the novelty of the work, if compared with previous articles, is to focus globally on the impacts that key technologies can produce on business functions in multiple areas and sectors. Third, the proposed framework has a greater number of practices analyzed than the other articles currently published.

III. Methodology

A. Framework for Investigating the Adoption of Key Technologies

The suggested framework aims at standardizing emerging practices collected from the systematic literature review. An

TABLE I
CLASSIFICATION OF KEY TECHNOLOGIES FROM SCIENTIFIC LITERATURE

Reference	Area	Technologies analyzed	No. of articles analyzed	No. of practices found
[46]	SCM	IoT	166	15
[43]	Industry 4.0	Industrial IoT	Not declared	6
[47]	SCM	3-D printing; Augmented reality; Big data; Cloud computing; IoT; Nanotechnology; Robotics; Self-driving vehicles; Sensor technology; Unmanned aerial vehicle	109	44
[8]	Industry 4.0	Augmented reality; CAD; Cloud-based manufacturing; Cyber–physical production system; Cyber–physical system; Digital twin; ERP; EIS; Industrial IoT; Internet of services; IoT; Industrial wearable system; Industrial wireless networks; RFID; Virtual reality	130	10
[4]	Manufacturing	AI; Augmented reality; Cyber–physical production system; Cyber–physical system; GPS; EDI; ERP; Industrial IoT; Internet of data; Internet of services; RFID; Virtual reality	608	10
[38]	Transportation	Additive manufacturing; CAD; EV batteries	Not declared	Not declared
[40]	Manufacturing	AI	91	13
[39]	Industry 4.0	Additive manufacturing	206	4
[48]	SCM	Blockchain	27	27
[41]	SCM	Blockchain	69	48
[6]	Agriculture	3D printing; AI Augmented reality; Autonomous systems; Big data and analytics; Cloud; Connectivity; Distributed ledger; Local and remote sensing; Social media	35	61

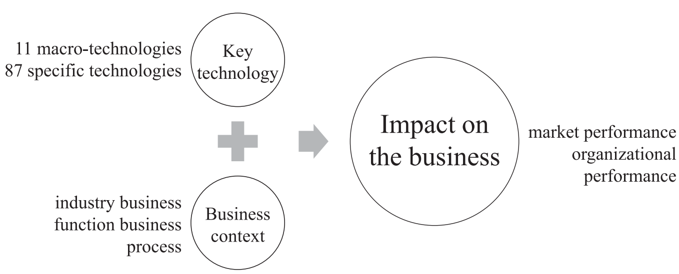


Fig. 1. Combination of variables linked to an emerging practice.

emerging practice consists of the implementation of one or more key technologies within a specific business context in order to enhance business performance. Therefore, to classify and standardize information extracted from the content analysis of the full text of each scientific paper, an emerging practice is recorded in a repository as the combination of various labels referring to key technology, business context of application, and expected impact in terms of performance enhancement (see Fig. 1).

This will allow the switch from text to categorical variables that is important to exploit information to perform analysis on the state-of-the-art of key technologies. In particular, the repository reports 87 specific key technologies, which are classified into 11 macrocategories. The context of application of the key technology within the focal emerging practice is defined with the industry of adoption of the practice, the business function that employs it, and the business process in which the technology is exploited. The variables associated with the business context are important. Indeed, emerging practices that employ key technologies are risky since there is not a consolidated implementation in businesses. To reduce such a risk, it is useful to define the boundaries of application of the technology by clarifying industry, business function, and business process where it can be used. As to the impact on the business performance, it can be either internal, i.e., the focal emerging practice enhances organizational performance, or external, i.e., improvements in terms of market performance can be achieved.

To demonstrate the usefulness of this research, once identified all emerging practices within the scientific articles under investigation, a machine learning algorithm belonging to association rule mining will be employed to identify within the sample the most frequent and relevant emerging practices that could become future best practices (see Fig. 2). Therefore, starting from the entire set of emerging practices, the algorithm will extract a subset of those that are less risky and are more likely to provide the expected impact on business performance, taking into account the business context where the key technology is implemented. The following sections will provide a formal description of each variable.

B. Taxonomy of Key Technologies

By employing an inductive approach [17], [18], a taxonomy of 11 categories of key technologies has been built. Although some classifications are already present in the literature [4], [8], these only consider certain groups of key technologies, as previously shown in Table I. On the contrary, this research has achieved a classification as the result of the study of thousands of scientific articles where hundreds of categories of technologies were detected. From this bottom-up procedure, specific technologies have been detected and then grouped by macrocategories. Table II presents the 11 macrocategories of key technologies that in total enclose 87 specific technologies.

The 3-D printing, or additive manufacturing, allows the construction of 3-D elements by adding material to create a

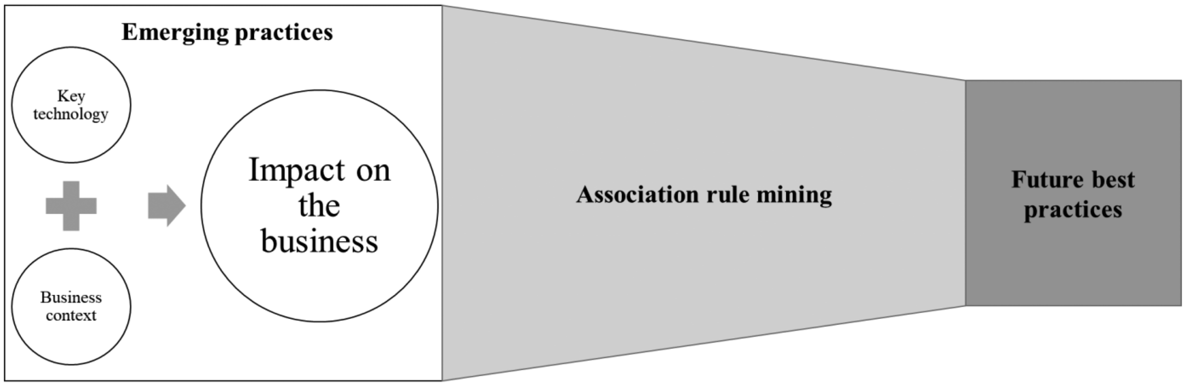


Fig. 2. From emerging practices to future best practices.

TABLE II
TAXONOMY OF KEY TECHNOLOGIES

Category	Examples of technologies included
3D printing	Binder Jetting; Bioprinting; Direct energy deposition; fused filament fabrication; fused deposition modeling; Laminated object manufacturing; Polyjet; Powder bed fusion; Stereolithography
AI	Artificial neural network; Classification algorithm; Computer vision; Deep learning; Metaheuristic Algorithm; Natural language processing; Regression algorithm; Reinforcement Learning; Unsupervised learning
Blockchain	Blockchain; Cryptocurrencies; NFT; Other distributed ledgers; Smart contracts
Computing	Cloud computing; Cloud storage; Cloudlet computing; Edge computing; Fog computing; Quantum computing
Digital applications	API/webservices; Chatbot; Contact center automation; Digitization technologies; Mobile applications; Robotic process automation; Social media and network; Web applications and platform
Geospatial technologies	Geographic information systems; Geospatial intelligence; Global navigation satellite system; Global positioning system; Remote sensing; Spatial analytics; Web mapping
Immersive environments	Augmented reality; Digital Human; Digital twin; Gamification; Holograms; Metaverse; Mixed reality; Virtual reality
IoT	IoT; 5G networks; Internet of Vehicles; LoRa; Mobile sensing; Smart sensors; Wearables; Wireless sensors
Open and crowd-based platforms	Crowdfunding platform; Crowdshipping platform; Crowdsourcing platform; Open access; Open data; Open innovation platform; Open science; Open source
Proximity technologies	Biometrics; Proximity sensors; Beacon; Bluetooth; Motion detectors; near-field communication; Qrcode/datamatrix; RFID
Robotics	Autonomous mobile robot; AS/RS; Autonomous (driverless) vehicles; Cobot; Industrial robot; Service robot; Unmanned aerial vehicle; Unmanned ground vehicles; Unmanned underwater vehicles; Wearable robot

customized geometry [51]. AI refers to intelligent agents capable of maximizing the chance of achieving goals, with cognitive, learning, and problem-solving capabilities [52]. Blockchain technology refers to decentralized and distributed digital ledgers consisting of blocks where transactions and information are recorded using a peer-to-peer network to guarantee inalterability and security of data [14]. Computing technologies enclose both quantum and cloud-based computing, where the former refers to technologies allowing great computational power, whereas the latter regards a set of information technologies based on on-demand availability of resources, such as storage and computing, which are distributed over multiple locations [53]. The digital applications category contains software, social networks, and digital tools, accessible from smartphones and browsers, which run on web servers and support paperless activities [54]. Geospatial technologies comprise instruments and tools to collect, process, and analyze geographic data [55]. Immersive environments collect technologies that allow immersion into virtual reality and nonphysical worlds or the employment of virtual instruments to enhance human perception within the real-world environment [56]. IoT technologies refer to connected physical devices or "things" equipped with sensors that collect and share information within a network over the internet [57]. Open and crowd-based platforms encompass a set of tools, applications, and platforms to employ open and crowd-based approaches, allowing access to information, data, knowledge, sources, software, as well as activities performed by people and citizens [58], [59], [60]. Proximity technologies refer to sensors, devices, and objects able to detect the presence of nearby elements without any physical contact [61]. Robotics category encloses innovative robots able to autonomously perform actions either partially or totally [62]. It also includes unmanned aerial vehicles [63]. The list has been continuously reviewed during data collection; therefore, the 87 specific key technologies are those predominant in the literature, whereas the grouping of technologies within the 11 macrocategories has followed the logic of technical and technological commonality, as well as similarities in terms of data management and performed actions. Indeed, from the one hand, technologies could change physical flows, performing or supporting specific actions. From the other hand, other technologies predominantly affect information flows. Table III summarizes the features of each key technology to show the complexity of the suggested classification. Regarding data management, key technologies can support data capture, data storage/transfer, or data processing. As to performed actions, technologies support simulation activities or perform an action with three opportunities: complete automation, support to human action, or execution of activities operated by humans.

C. Business Context: Industry

The methodology takes into account 54 industries in primary, manufacturing, and tertiary sectors (see Table IV). To guarantee the comprehensiveness of the classification, the labels have been checked with other standard classifications, such as the standard

TABLE III
FEATURES OF KEY TECHNOLOGIES IN TERMS OF DATA MANAGEMENT AND PERFORMED ACTION

	Data management			**Performed action**			
	Data capture	*Data storage/ transfer*	*Data processing*	*Simulation*	*Automation*	*Supporting human action*	*Operated by humans*
3D-printing							X
AI			X	X	X	X	
Blockchain		X					
Computing		X	X				
Digital applications	X					X	X
Geo-spatial tech	X	X	X	X		X	
Immersive environments				X		X	
IoT	X	X					
Open and crowd-based platforms	X					X	X
Proximity tech	X					X	
Robotics					X	X	X

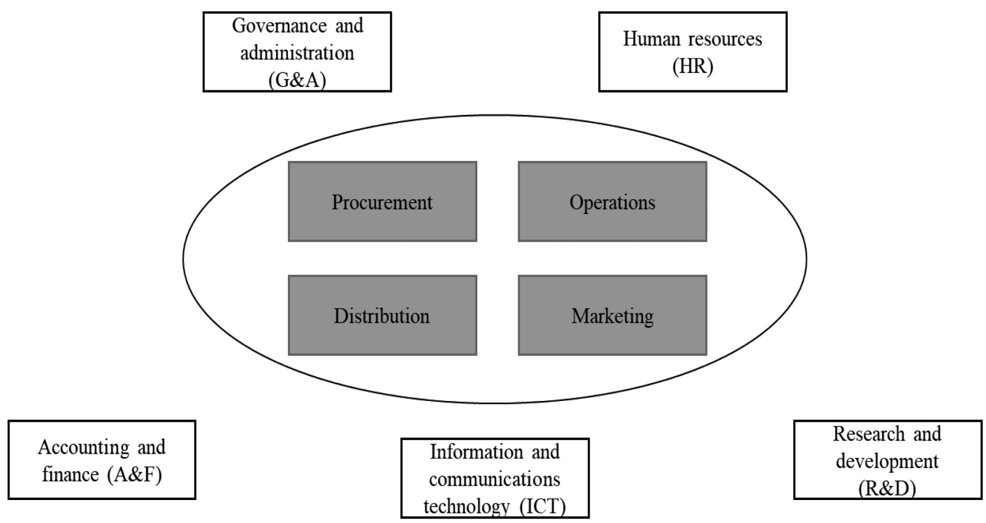


Fig. 3. Primary and secondary business functions considered within the framework.

industrial classification (SIC) codes [64]. The variable also considers a general category for "horizontal" applications that can be employed in all sectors. Therefore, the framework is suitable to support the choice of implementation of key technologies in all industries, whereas many systematic literature reviews focus on specific industries. In particular, for the primary sector, four different industries are found, the manufacturing sector is characterized by 21 industries, while the tertiary sector reports 25 labels. Three additional labels, one for each sector, refer to a general usefulness within the specific sector. For instance, manufacturing (general) encloses emerging practices that are useful for all industries within the manufacturing sector.

D. Business Context: Business Function and Business Process

In the literature, there are several articles discussing key technologies without referring to a specific business function but within general areas, such as SCM [65], [66] or Industry 4.0 [3], [67]. Some of these articles focus on specific processes, such as the use of key technologies in product design [68] or R&D projects [69], [70], [71]. However, this work aims to investigate all the different business functions and not focus only on some specific areas. Therefore, companies could decide to use key technologies by precisely identifying the business function concerned. Indeed, key technologies may have effects on companies even within apparently secondary and less discussed business functions. Hence, it is essential to define the area of implementation of these technologies. Actually, the business function specifies where the emerging practices can be carried out. In particular, both primary and support functions are considered (see Fig. 3). For each business function, a list of business processes is reported (see Table V). Therefore, the variable business process can be considered as a specific subcategory of the business function, aiming at better delineating where the emerging practice can be implemented. A set of 43 business processes is suggested, also considering one label for the business function *general*, which is assigned to practices that are implemented within all parts of the organization. The

TABLE IV
LIST OF INDUSTRIES BY SECTOR REPORTED WITHIN THE FRAMEWORK

Sector	**Industry**	**SIC Codes**
General	General	
Primary	Primary (general)	
	Agriculture	01110; 01120; 01130; 01140; 01150; 01160; 01190; 01210; 01220; 01230; 01240; 01250; 01260; 01270; 01280; 01290; 01300; 01410; 01420; 01430; 01440; 01450; 01460; 01470; 01490; 01500; 01610; 01621; 01629; 01630; 01640.
	Fishing	03110, 03120; 03210; 03220.
	Mining	05101; 05102; 05200; 06100; 06200; 07100; 07210; 07290; 08110; 08120, 08910; 08920; 08930; 08990; 09100; 09900.
	Wood	01700; 02100; 02200; 02300; 02400.
Manufacturing	Manufacturing (general)	
	Aerospace and aeronautics	30300; 33160.
	Automotive	29100; 29201; 29202; 29203; 29310; 29320.
	Biomedical	26600; 32500; 32910.
	Ceramic	23310; 23410; 23420; 23430; 23440; 23490
	Chemical	20110; 20120; 20130; 20140; 20150; 20160; 20170; 20200; 20301; 20302; 20411; 20412; 20420; 20510; 20520; 20530; 20590; 20600.
	Construction	16100; 16210; 16220; 16230; 16240; 16290; 23510; 23520; 23610; 23620; 23630; 23640; 23650; 23690; 23700; 23910; 23990; 41100; 41201; 41202; 42110; 42120; 42130; 42210; 42220; 42910; 42990; 43110; 43120; 43130; 43210; 43220; 43290; 43310; 43320; 43330; 43341; 43342; 43390; 43910; 43991; 43999.
	Defense	30400
	Electric power	27110; 27120; 27200; 27310; 27320; 27330; 27400; 27510; 27520; 27900.
	Electronics	26110; 26120; 26200; 26301; 26309; 26400; 26511; 26512; 26513; 26514; 26520; 26701; 26702; 26800; 33130; 33140; 95110; 95120; 95210.
	Energy	35110; 35120; 35130; 35140; 35210; 35220; 35230; 35300.
	Food and beverage	10110; 10120; 10130; 10200; 10310; 10320; 10390; 10410; 10420; 10511; 10512; 10519; 10520; 10611; 10612; 10620; 10710; 10720; 10730; 10810; 10821; 10822; 10831; 10832; 10840; 10850; 10860; 10890; 10910; 10920; 11010; 11020; 11030; 11040; 11050; 11060; 11070; 12000.
	Furniture	31010; 31020; 31090
	Glass	23110; 23120; 23130; 23140; 23190
	Jewellery	32120; 32130;
	Machinery production	28110; 28120; 28131; 28132; 28140; 28150; 28210; 28220; 28230; 28240; 28250; 28290; 28301; 28302; 28410; 28490; 28910; 28921; 28922; 28923; 28930; 28940; 28950; 28960; 28990; 33120; 33200.
	Paper and pulp	17110; 17120; 17211; 17219; 17220; 17230; 17240; 17290; 18110; 18121; 18129; 18130; 18140.
	Petroleum	19100; 19201; 19209.
	Pharmaceutical	21100; 21200.
	Steel	24100; 24200; 24520; 25910
	Textile	13100; 13200; 13300; 13910; 13921; 13922; 13923; 13931; 13939; 13940; 13950; 13960; 13990; 14110; 14120; 14131; 14132; 14141; 14142; 14190; 14200; 14310; 14390; 15110; 15120; 15200.
	Toys	32401; 32409
Tertiary	Services (general)	
	Beauty	96020
	Betting	92000
	Cleaning	81210; 81221; 81222; 81223; 81229; 81299;
	Consulting and professional services	69101; 69102; 69109; 69201; 69202; 69203; 70100; 70210; 70221; 70229; 71111; 71112; 71121; 71122; 71129; 71200; 72110; 72190; 72200; 73110; 73120; 73200; 74100; 74201; 74202; 74203; 74209; 74300; 74901; 74902; 74909; 74990; 78109; 78200; 78300; 80100; 80200; 80300; 81100; 81300; 82110; 82190; 82200; 82301; 82302; 82911; 82912; 82920; 82990; 84110; 84120; 84130; 84210.
	Digital	18201; 18202; 18203.
	e-Commerce	47910.
	Education	85100; 85200; 85310; 85320; 85410; 85421; 85422; 85510; 85520; 85530; 85590; 85600; 91011.
	Entertainment	59111; 59112; 59113; 59120; 59131; 59132; 59133; 59140; 59200; 60100; 60200; 78101; 90010; 90020; 90030; 90040.
	Fashion	46160; 46420; 47710; 47820.
	Financial services	64110; 64191; 64192; 64201; 64202; 64203; 64204; 64205; 64209; 64301; 64302; 64303; 64304, 64305; 64306; 64910; 64921; 64922; 64929; 64991; 64992; 64999; 65110; 65120; 65201; 65202; 65300; 66110; 66120; 66190; 66210; 66220; 66290; 66300.
	Healthcare	75000; 86101; 86102; 86210; 86220; 86230; 86900; 87100; 87200; 87300; 87900; 88100; 88910; 88990.
	Hotels and accommodation	55100; 55201; 55202; 55209; 55300; 55900.
	News media	58110; 58120; 58130; 58141; 58142; 58190.
	Passenger transport	49100; 49311; 49319; 49320; 49390; 50100; 50300; 51101; 51102; 51220; 52213.
	Real estate	68100; 68201; 68100; 68201; 68202; 68209; 68310; 68320; 68202; 68209; 68310; 68320.
	Restaurant and café	56101; 56102; 56103; 56210; 56290; 56301; 56302.
	Retail	45111; 45112; 45190; 45200; 45310; 45320; 45400; 46110; 46120; 46130; 46140; 46150; 46170; 46180; 46190; 46210; 46220; 46230; 46240; 46310; 46320; 46330; 46341; 46342; 46350; 46360; 46370; 46380; 46390; 46410; 46431; 46439; 46440; 46450; 46460; 46470; 46480; 46491; 46499; 46510; 46520; 46610; 46620; 46630; 46640; 46650; 46660; 46690; 46711; 46719; 46720; 46730; 46740; 46750; 46760; 46770; 46900; 47110; 47190; 47210; 47220; 47230; 47240; 47250; 47260; 47290; 47300; 47410; 47421; 47429; 47430; 47510; 47520; 47530; 47540; 47591; 47599; 47610; 47620; 47630; 47640; 47650; 47721; 47722; 47730; 47741; 47749; 47750; 47760; 47770; 47781; 47782; 47789; 47791; 47799; 47810; 47890; 47990; 77110; 77120; 77210; 77220; 77291; 77299; 77310; 77320; 77330; 77341; 77342; 77351; 77352; 77390.
	Software	58290; 62011; 62012; 62020; 62030; 62090; 63110; 63120; 63910; 63990.
	Sport, fitness and wellness	93110; 93120; 93130; 93191; 93199; 96040.
	Telecommunication	61100; 61200; 61300; 61900.
	Tourism	79110; 79120; 79901; 79909; 91012; 91020; 91030; 91040; 93210; 93290.
	Transportation and logistics	49200; 49410; 49420; 49500; 50200; 50400; 51210; 52101; 52102; 52103; 52211; 52212; 52219; 52220; 52230; 52241; 52242; 52243; 52290; 53100; 53201; 53202.
	Videogame	58210.
	Waste	38110; 38120; 38210; 38220; 38310; 38320; 39000.
	Water	36000; 37000.

TABLE V
LIST OF BUSINESS PROCESSES BY BUSINESS FUNCTION REPORTED WITHIN THE FRAMEWORK

Business function	**Business process**
General	General
Accounting and finance	Accounting and auditing; Credit risk and financial monitoring; Financial transactions; Investments evaluation
Distribution	3PL 4PL Couriers – Outsourcing; Delivery; Distributors and wholesalers; Inventory; Reverse logistics; Transportation; Warehouses
Governance and administration	Business monitoring; Decision making; Strategic planning
Human resources	Human resources management; Recruitment and selection; Training–education–organizational culture; Work health and safety
Information and communications technology	Database and data management; Software and information systems; Telecommunication and network services
Marketing	Advertising, communication, and promotion; Customer payment; Customer service; Market analysis; Postsale service; Sales and sales channels
Operations	Maintenance and diagnostics; Operations control; Operations planning; Plant services; Production of goods; Provision of services; Quality management
Procurement	Buyer–supplier relationships; Order management–purchasing; Raw materials management; Supplier evaluation and selection; Supplier payment
Research and development	Product design and development; Product innovation; Prototyping

TABLE VI
LIST OF IMPACTS REPORTED WITHIN THE FRAMEWORK

External performance	**Internal performance**
Attracting investors	Costs reduction
Brand reputation	Efficiency and productivity
Competitive advantage	Employee engagement
Customer satisfaction	Energy efficiency
Government incentives	Flexibility
Product/service quality/value/differentiation	Information management
Revenues	Innovation, knowledge, and technology management
	Risk reduction
	supply-chain relationships management
	Time reduction

variables are useful to improve the applicability of the framework to multiple types of analyses. For instance, to study the relationship between SCM and key technologies, it is useful to select specific processes within the four functions distribution, marketing, operations, and procurement. Moreover, the identification of the process that will employ the key technology is indispensable to delineate the area of application where it is possible to achieve the expected positive impact on the business performance. The same technology used in a different process could not provide the same positive impact.

E. Impact on Business Performance

This variable delineates the impact of key technologies on the business. In particular, an emerging practice could affect either *external* or *internal* performance (see Table VI). The first refers to performance improvements of external relationships with clients, investors, and stakeholders in general so that it is possible to link the adoption of a key technology with positive impacts on the market. The latter concerns internal positive effects of the implementation of key technologies within the organization, with positive effects in terms of time, costs, productivity, and resource efficiency. As follows, an explanation of all labels is provided.

External performance encloses *attracting investors* since key technologies enhance financial attractiveness [72] and can improve financial performance [73], long-term shareholder value [74], or stock price performance [75]. Moreover, higher external performances can be achieved in terms of *brand reputation* [76], *competitive advantage* [77], *customer satisfaction* [78], and *product/service quality/value/differentiation* [79]. Finally, the label *revenues* enclose all emerging practices that support selling activities or sales growth [80].

Internal performance is associated with positive impacts within business processes and activities, covering *cost reduction* [81], *efficiency and productivity* (e.g., reliability, waste reduction, and productivity) [82], *energy efficiency* gains [83], *flexibility* in production and design [84], and *time reduction* [85]. Moreover, it comprises the optimization of management activities associated with critical issues of a business, such as *employee engagement* [86], *information management* (e.g., traceability, better-informed decisions, control, real-time visibility, transparency, and monitoring) [5], *innovation, knowledge and technology management* (e.g., technological development, product innovation, digitalization, and access to new knowledge) [87], *risk reduction* (e.g., security and privacy issues, reduction of accidents at work, and reduction of fraudulent behaviors) [88], and *supply-chain relationships management* (e.g., integration, coordination, collaboration, information sharing, and transparency among partners) [89], [90].

F. Data Collection From Scientific Articles

Brooks argued that one of the ways in which science contributes to technology is creating an important knowledge base in evaluating technology in terms of social, environmental, and strategic business impacts and identifying industrial practices [16]. Recently, the rapid growth of science and technology has increased the complexity of managing these two issues. Fortunately, the parallel growth of information in both science and technology offers the possibility of advanced decision support to guide the activities to be carried out. In general, scientific research tends to anticipate the technology; therefore, academic researchers, policymakers, industrialists, and consultants could employ literature to plan and program decisions on the adoption of key technologies [15]. In particular, case studies are used to evaluate the advantages and disadvantages of key technologies [91], [92]. One reason for the case study being recognized as a research method is that researchers were becoming increasingly concerned about the limitations of quantitative methods in providing the in-depth explanations of how much key technologies impact on business [93]. As key technologies are not adopted by most companies, their real benefits and disadvantages are hidden [94]. Through case study methods, a researcher is able to go beyond quantitative statistical results and understand the dynamics that key technologies may change [95]. Case studies help to explain both the process and the outcome of a phenomenon through the observation, reconstruction, and analysis of the cases under investigation [96]. For this reason, scientific research often presents case studies in which key technologies are implemented and this can be useful for generalizing emerging practices [97].

Therefore, in order to ensure the widest coverage level and the continuous update, emerging practices are extracted from

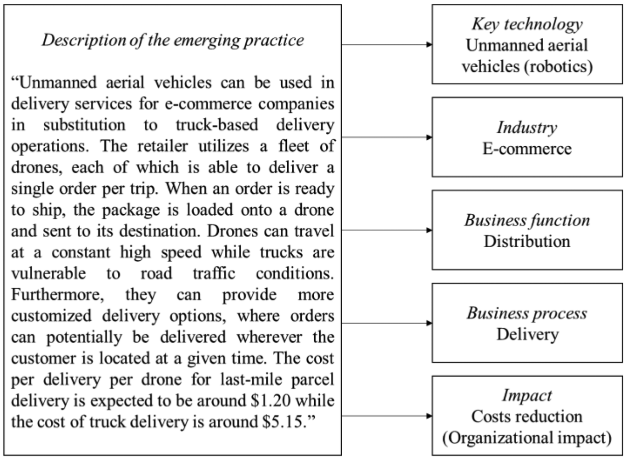


Fig. 4. Example of classification of an emerging practice.

the analysis of scientific papers. Indeed, some scholars have already used scientific papers as a source to detect emerging trends in the adoption of new technologies and practices, as well as other contributions have built lists of emerging practices from the review of relevant literature [98], [99]. However, this work intends to perform a systematic literature review in order to standardize information from scientific papers and provide the state-of-the-art of the overall implementation of emerging practices, useful not only for scientific purposes but also for managerial and organizational ones. The methodology of systematic literature review is particularly suitable for this research since it allows summarizing the evidences from primary studies through a formal research protocol. Being papers the source of information, it is necessary to read the full text, analyze the content, and process each document to assign standardized variables to each emerging practice. In particular, a cloud-based web application has been implemented to allow researchers in the field of technology, operations, and management to perform the activity. The researcher reads and analyzes the full text of each scientific paper, searching for emerging practices that employ new technologies. Since the identification of emerging practices is complex within the full text and the required information could be scattered within the document, it is not possible to implement an automatic script and natural language processing techniques to perform the process, but human interpretation is necessary. To record a practice, it is necessary to assign labels for each variable (i.e., key technology, industry, business function, business process, and impact). These predefined variables and labels guarantee data standardization and comparability. However, to assign labels, it is necessary to have a significant experience on technical and technological issues. Moreover, when the user detects new potential labels to assign to the variables, he/she can suggest the addition of a new element. Indeed, flexibility is necessary because new practices and technologies could manifest original features to add to the initial set of labels. The only "free" input field is the textual description of the emerging practice, where the researcher clarifies usefulness, aim, implementation, and peculiarities of the focal practice. In this way, activities, supported operations, and data employed can be better clarified. Fig. 4 shows an example of acquisition of information from the work presented by Chen et al. [100], where an application of last mile delivery using drones is suggested. From the content analysis of the full text and the further classification, the emerging practice is summarized by the combination *key technology-industry-business function-business process-impact-description*. After an additional perspective, by considering only categorical variables, each emerging practice is expressed by the tuple *key technology-industry-business function-business process-impact*.

The starting list of scientific papers consists of contributions published from January 2019 to July 2022 in the most relevant journals in the field of business, finance, economics, management, operations research, management science, and accounting, according to ISI Web of Science and Scimago Journal Ranking, focusing on journals reported in either Q1 or Q2 in at least one of the sources. Then, the list of scientific papers was searched on SCOPUS by creating a specific search query for each technology. In particular, for each key technology, specific contents, which refer to either the category or the specific technologies, are searched within title and keywords fields. For instance, the following query was used to search for papers investigating immersive environments: *(TITLE ("immersive environments") OR KEY ("immersive environments") OR TITLE ("augmented reality") OR KEY ("augmented reality") OR TITLE ("digital human") OR KEY ("digital human") OR TITLE ("holograms") OR KEY ("holograms") OR TITLE ("metaverse") OR KEY ("metaverse") OR TITLE ("virtual reality") OR KEY ("virtual reality") OR TITLE ("mixed reality") OR KEY ("mixed reality") OR TITLE ("digital twin") OR KEY ("digital twin") OR TITLE ("gamification") OR KEY ("gamification"))*.

The researchers search for a paper, and then manually read and study the entire document, with three available options: paper not found, paper not useful, or paper useful. The first regards documents whose electronic version is not downloadable from the Internet, whereas the second regards papers where no business practices were found. Indeed, an important ratio of not useful documents is found since many papers focus on the "policymaker" or "macroeconomic" perspective, as well as on "technological" and "technical" issues of key technologies. The paper is considered useful only if it presents the implementation of an emerging practice. To add an emerging practice, the information extracted from the paper has to provide a clear association with all variables under investigation. When not sufficient detail is provided, the practice is disregarded. Furthermore, practices are recorded only if there is an exhaustive description of their functioning, which data employ, why they are used, which is the aim of implementing them, how they allow the firm achieving goals and enhance business performance, who employs the technology, and why they are different from traditional practices. Scientific papers were assigned to only one researcher at a time, but at the end of the analysis, a second researcher (i.e., reviewer) revised the analysis of the colleague. Eventual doubts regarding the labels assigned are solved with a joint activity of the researcher and the reviewer.

At the end of July 2022, the number of searched papers is 22 337 on a total of about 50 000 documents deriving from the sum of the results of 11 queries on SCOPUS. Therefore, the investigated sample is statistically significant to provide an overview of the state-of-the-art of key technologies. In particular, 1165 documents were not available on the Internet, whereas 21 172 were downloaded and examined for a ratio of about 95% of searched papers. Among the analyzed papers, 5442 report at least an emerging practice, i.e., one-fourth of available documents (see Fig. 5). More than 100 man months were necessary to perform the research, engaging 10 researchers

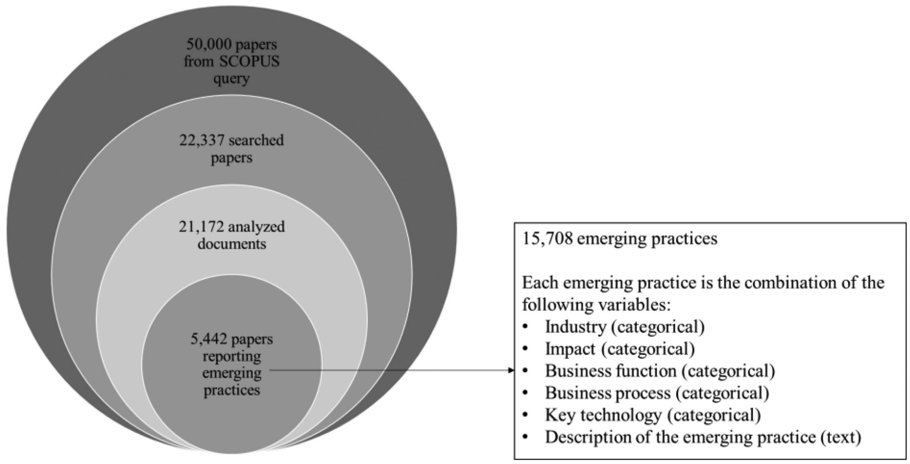


Fig. 5. Output of the systematic literature review on emerging practices.

expert in the field of engineering and technology management from January 2020 to July 2022. The final sample consists of 15 708 different combinations *key technology-industry-business function-business process-impact-description*. Since the same labels for categorical variables can be the same for multiple emerging practices, by considering only the distinct number of tuples, *key technology-industry-business function-business process-impact* the dataset reports 11 049 elements. It is interesting to consider that the potential number of available combinations is about 3.4 million, i.e., 87 technologies $\times$ 54 industries $\times$ 43 processes $\times$ 17 impacts. This means that, to date, the share of possible combinations that have been already found a real implementation is 0.32%, underscoring that a minimal part of the available combinations has been already explored in the literature and practice. This also underlines the high unexpressed potential value of key technologies.

The journals exhibiting the larger number of useful papers are: *Applied Energy, Applied Sciences, Computers and Industrial Engineering, Computers in Industry, Energy, Expert Systems With Applications*, IEEE SYSTEMS JOURNAL, IEEE TRANSACTIONS ON ENGINEERING MANAGEMENT, *International Journal of Production Research, Journal of Business Research, Journal of Cleaner Production, Journal of Manufacturing Systems, Knowledge-Based Systems, PLoS ONE, Resources, Conservation and Recycling, Robotics and Computer-Integrated Manufacturing, Science of the Total Environment, Scientific Reports*, *Technological Forecasting and Social Change*, and *Transportation Research Part C: Emerging Technologies*.

IV. FINDINGS

To let emerge the explicative power of the methodology, this section presents an exploratory study on the repository of 15 708 emerging practices. First, descriptive statistics of each categorical variable are presented to provide a general overview of the state-of-the-art. Second, an explorative analysis is carried out in order to detect the most frequent and robust combinations of labels that define which are the emerging practices that are the best candidates to become future best practices. The analysis is performed by implementing a machine learning algorithm belonging to the category of association rule mining.

A. Descriptive Statistics

In this section, a first analysis of the distribution of practices for each categorical variable is presented. Table VII presents the number of practices employing key technologies. It reports both the macrotechnology and, for short, only the belonging specific technologies that cover at least 1% of the entire dataset. *AI* is the most frequent and covers about one-third of the emerging practices; also *blockchain*, *robotics,* and *digital applications* are associated to many opportunities of implementation.

Table VIII presents the top industries that cover more than 1% of the entire dataset. About 15% of practices are associated with the general adoption within the entire manufacturing sector, which is the natural habitat for key technologies deriving from Industry 4.0 paradigm. It is interesting to underscore the significant value associated with the healthcare industry, which confirms the relevance of "health technologies," as well as the wide range of opportunities for implementation of key technologies in the field of transportation.

To summarize the relationship between emerging practices and industry of application, Table IX groups practices by sectors, underscoring that manufacturing and tertiary are featured by a larger number of emerging practices compared with the primary sector.

Moreover, Table X presents the count of practices by business function. In addition, only the belonging business processes covering at least 1% of the total number of practices are reported. It is interesting to underscore that the practices permeate all business functions. Even though many of them are associated with primary functions, such as operations and distribution, results show that the adoption of key technologies could provide opportunities for business performance improvement also within ancillary functions. Since most of the research on key technologies is focused on SCM, results suggest expanding and investigating the implementation toward secondary areas, such as accounting and finance, human resources management, and governance and administration. As to the most frequent processes, operations planning, and control, production of goods and provision of services are prevailing, confirming the significant weight of the operations function, which covers about 50% of the total number of emerging practices.

TABLE VII
EMERGING PRACTICES BY MACROCATEGORY OF KEY TECHNOLOGIES AND SPECIFIC KEY TECHNOLOGY

Technology	#	Technology (continued)	#
AI	***4 990***	***IoT***	***1 280***
artificial neural network	1 070	IoT	681
classification algorithm	939	smart sensors	299
deep learning	966	others	300
metaheuristic algorithm	525	***Geospatial tech***	***1 137***
natural language processing	288	GIS geographic information systems	531
regression algorithm	585	GPS global positioning system	350
reinforcement learning	179	remote sensing	185
unsupervised learning	384	others	71
others	54	***Immersive environments***	***959***
Blockchain	***1 520***	augmented reality	254
blockchain	1 011	digital twin	329
smart contracts	420	virtual reality	253
others	89	others	123
Robotics	***1 472***	***Computing***	***901***
autonomous (driverless) vehicles	352	cloud computing	576
industrial robot	221	others	325
service robot	188	***Proximity tech***	***878***
unmanned aerial vehicle	449	RFID	488
others	262	others	390
Digital applications	***1 370***	***Open and crowd-based platforms***	***773***
mobile applications	323	crowdsourcing platform	252
social media and network	508	open source	266
web applications and platform	269	others	255
others	270	***3D printing***	***428***
		Total	**15 708**

The boldface is used to signal the existence of macrocategories.

TABLE VIII
TOP INDUSTRIES REPORTING EMERGING PRACTICES

Industry	#
Manufacturing (general)	2 479
Healthcare	1 528
General	1 366
Transportation and Logistics	1 237
Passenger transport	848
Electric power	657
Agriculture	646
Energy	641
Automotive	562
Food and Beverage	562
Construction	525
Retail	467
E-commerce	418
Financial services	345
Tourism	309
Water	285
Digital	239
Services (general)	217
Electronics	202
Restaurant and cafè	181
Aerospace and Aeronautics	172
Hotels and accommodation	171
Other industries	1651
Total	**15 708**

TABLE IX
EMERGING PRACTICES BY SECTOR

Sector	#
General	1 366
Primary	893
Manufacturing	6357
Tertiary	7092
Total	**15 708**

Regarding the impact on business performance, about 20% of practices allow efficiency and productivity enhancements, but also costs reduction and improvements in terms of information management cover a significant share. Yet, key technologies are also able to enhance customer satisfaction and product/service quality/value/differentiation. Grouping emerging practices by impact areas results show that improvements in terms of internal performance feature over 75% of emerging practices (see Table XI).

B. Explorative Analysis of Emerging Practices

In order to exhibit the opportunity deriving from the implementation of the methodology, an explorative analysis of the emerging practices is presented. Since the dataset consists of categorical variables, text mining techniques employing machine learning algorithms have been preferred. The use of

TABLE X
EMERGING PRACTICES BY BUSINESS FUNCTION AND PROCESS

Business function - business process	#	Business function - business process (continued)	#
Operations	***7 615***	***Research and development (R&D)***	***721***
Operations control	163	Product design and development	396
Provision of services	1 867	Product innovation	254
Production of goods	1 288	others	71
Operations planning	1 049	***ICT***	***704***
Maintenance and diagnostics	726	Database and data management	523
Quality management	400	others	181
others	122	***Governance and administration (G&A)***	***526***
Distribution	***2 179***	Strategic planning	272
Delivery	711	Decision making	167
Transportation	532	others	87
Warehouses	331	***Human resources (HR)***	***471***
Inventory	282	Work health and safety	180
others	323	Human resources management	167
Marketing	***2 081***	others	124
Market analysis	912	***Accounting and finance (A&F)***	***393***
Customer service	442	***General***	***120***
Advertising, communication and promotion	421		
Sales and sales channels	194		
others	112		
Procurement	***898***		
Buyer–supplier relationships	410		
Order management - purchasing	217		
Supplier evaluation and selection	125		
others	146	**Total**	**15 708**

The bold entities is used to signal the existence of macrocategories.

TABLE XI
EMERGING PRACTICES BY IMPACT ON THE BUSINESS PERFORMANCE

Impact	#	Impact (continued)	#
Internal	***11 903***	***External***	***3805***
Efficiency and productivity	3496	Customer satisfaction	344
Costs reduction	1833	Product/service quality/value/differentiation	261
Information management	1781	Competitive advantage	434
Risk reduction	1414	Revenues	416
Time reduction	1023	Brand reputation	210
Supply-chain relationships management	1000	Attracting investors	125
Energy efficiency	582	Government incentives	15
Innovation, knowledge, and technology management	341		
Flexibility	335		
Employee engagement	98	**Total**	**15 708**

Reports on the left the impact macrocategory "internal" with the belonging sub-categories, while on the right the macrocategory "external" is reported with their belonging elements in the subsequent rows.

machine learning for data analytics is growing in the literature and practice since it allows finding patterns among variables. In particular, emerging practices are featured by tuples *industry-business function-business process-key technology-impact*. This means that emerging practices are summarized as the use of a technology within a specific business context in order to achieve a specific impact on the business performance. Hence, the aim of this section is to show the most interesting combinations of variables that can be considered valuable, robust, and with the higher likelihood of achieving the expected impact, i.e., the "top emerging practices." In other words, with this section, the following question is answered:

Which are the most frequent and relevant emerging practices that could become future best practices?

To find the most interesting combinations, association rule mining techniques have been employed. This research uses the frequent-pattern growth algorithm (FP-Growth), a tree-based mining method proposed by Han et al. [101], which can extract frequent groups of items and association rules from large datasets. An itemset is a group of one or more items that are found together in the dataset. If a subset of elements *X* is extracted from an itemset, it is possible to predict the probability of finding the remaining elements *Y*. This relationship is an association rule, which is logically expressed as the following implication:

$$\{X\} \rightarrow \{Y\}.$$

The set *X* is the antecedent and *Y* is the consequent. The combination {*X, Y*} is transformed into an association rule where the occurrence of $\{X\}$ is associated to the presence of $\{Y\}$.

Association rules can select the most interesting itemsets by exploiting two variables, i.e., support and confidence [102]. Indeed, once determined the list of itemsets, the support count (*#s*) can be estimated as the frequency of occurrence of each itemset in the dataset. Moreover, the parameter confidence (*c*) can be calculated as the ratio of the sum of the dataset containing the set of *X* U *Y* itemsets on the count of records reporting the set of *X* item [103]. In line with this framework (see Fig. 1), the antecedent consists of the technology within the business context, whereas the consequent is the impact on business performance

$$\{\text{technology}, \text{ business context}\} \rightarrow \{\text{impact}\}.$$

Hence, the occurrence of a technology within a business context is associated with the presence of a specific impact. The number of occurrences in which the combination {technology, business context, impact} appears in the database is *#s*, whereas the likelihood of finding {impact} as the consequent when the antecedents are {technology, business context} is *c*.

In particular, the variable key technology can be expressed by either considering the 11 macrocategories or the 87 specific elements, whereas the business context can be defined with industry, business function, and business process. Moreover, the impact can be expressed by either the 17 labels presented in Section III-D or the two macrocategories, i.e., external and internal performance. In consideration of the features of association rule mining, for this exploratory research, the technology is represented through the 11 macrocategories, whereas the business context is summarized by the variables industry and business process. As to the impact, to simplify the representation of the results, the tradeoff between the external and internal performance is preferred.

$$\{\text{macrotechnology}, \text{ industry}, \text{ business process}\} \\ \rightarrow \{\text{macroimpact}\}.$$

In terms of the potential number of possible combinations, with this group of categorical variables, the maximum output is of 51 084 elements, i.e., 11 macrotechnologies $\times$ 54 industries $\times$ 43 processes $\times$ 2 impacts.

By implementing the FP-growth algorithm, it is possible to find out the most useful rules that suggest the implementation of a particular technology within a business context in order to enhance business performance. To extract the most interesting rules, only those satisfying minimum thresholds for support and confidence are considered. In particular, the threshold support value (*#s*) was set as 10, whereas the threshold confidence value (*c*) is 0.50. This allows to select the most frequent rules (*#s*) that are relevant for each antecedent (*c*). The FP-growth algorithm starts defining the frequent itemsets and creates the FP-tree, and then it scans each node of the three in order to find interesting rules according to the two thresholds. To launch the algorithm, a PHP web application has been implemented. Results show 879 associations, but only 262 are considered for the analysis. The other are nonsignificant since they either report other variables as the consequent or not all the three expected elements are reported as antecedents. By considering the potential number of possible combinations, the captured associations cover 0.51%. Since this research focuses on emerging practices, which are risky and costly to implement, this limited group of emerging practices is the perfect candidate for future best practices. This is possible, thanks to the joint effect of the support threshold and confidence threshold. The support threshold allows considering the most frequent combinations, i.e., the best combinations are those that have been mostly tested and applied in the literature. The confidence threshold supports the selection of only those combinations {macrotechnology, industry, business process} that have a likelihood higher than 50% of achieving a specific impact on the business performance, hence neglecting the combinations exhibiting the less likely impacts.

From the analysis of the extracted rules, a general consideration is that only about 10% of associations suggest an impact on external performance, hence delineating a prevalent stability of enhancement of internal performance when key technologies are implemented in organizations. Moreover, at least a combination for each macrotechnology has been found, even though those reporting AI, blockchain, and IoT are prevailing. As to industries, 29 out of 54 elements report at least an emerging practice, with labels *general* and *manufacturing (general)* covering about one-third of the association rules. A total of 32 out of 43 processes have been reported within association rules, with a prevalence of those within business function *operations*. As follows, for each macrotechnology, the list of combinations is reported and commented on.

The 3-D printing will allow new production methodologies and opportunities to improve internal performance in manufacturing industries in general as well as specific applications in R&D intensive sectors featured by market and product complexity are growing (see Table XII). In particular, some 3-D printing processes allow the production of pieces with superior mechanical features in a reduced time, useful for aerospace and automotive applications. Moreover, in the biomedical industry, 3-D printing is the optimal solution to manufacture components with biocompatible materials and antibacterial properties that are designed with advanced 3-D modeling software in order to be totally customized with the specifics of each patient. It is also useful in industries, such as healthcare, where it is necessary to fabricate parts and instruments quickly and locally to satisfy the variable and difficult-to-forecast product demand with a limited lead time. Additional interesting applications regard the opportunity of manufacturing houses and buildings through additive manufacturing. Moreover, 3-D printing is useful for design and rapid prototyping since it ensures flexibility and the development of complex geometries, minimizing material consumption and waste generation.

TABLE XII
3-D PRINTING—TOP EMERGING PRACTICES

Industry	Business Process	Impact macro category	Confidence
Construction	Production of goods	Internal	0.93
Electronics	Production of goods	Internal	0.89
Healthcare	Production of goods	Internal	0.84
Energy	Production of goods	Internal	0.83
Manufacturing (general)	Prototyping	Internal	0.83
Aerospace and Aeronautics	Production of goods	Internal	0.81
Automotive	Production of goods	Internal	0.74
Manufacturing (general)	Production of goods	Internal	0.73
Biomedical	Production of goods	Internal	0.57

AI reports 84 distinct association rules, covering one-third of the entire list (see Table XIII). It is doubtless a priority technology for emerging practices, covering 27 industries and 21 business processes. It is implementable within all business functions, from primary to ancillary. For instance, within the governance and administration function, AI can be employed to generate scenarios, estimate the performance of assets, and support decision making and planning. AI is the most promising technology to implement smart manufacturing systems and optimize SCM, but it is also useful for the tertiary sector. It is capable of analyzing information and data and exploiting them to revolutionize how services are provided. Even though it will support companies in enhancing their internal performance, in some industries, emerging practices employing it to achieve external performance are growing. In particular, AI is used for market analysis. Blockchain technology is very promising, especially for the manufacturing sector (see Table XIV). It positively affects internal impact, mainly in three areas. First, it is possible to find blockchain applications for the management of supply-chain operations. It reduces transaction-based costs, solves trust issues, improves real-time traceability, and protects product counterfeiting. Second, blockchain affects financial transactions with both the adoption of cryptocurrencies and the implementation of smart contracts to achieve automatic payment. Third, it adds security to data, changing management policies. For instance, blockchain defends companies against insider attacks and alteration of records, providing accessibility, authenticity verification, authorization, and security to information and preserving the privacy of employees, partners, clients, and devices. Its architecture is scalable and highly efficient and provides new instruments for management, processing, and control of large data traffic from people and devices.

Computing technologies change the way in which data are stored, shared, and processed (see Table XV). From the one hand, the entire manufacturing sector can rely on these technologies to improve operations. Computing technologies, such as cloud and edge computing, allow efficient and real-time data transmission and processing, which are necessary features to monitor processes in real time, detect issues, maintain high productivity, and optimize production scheduling. Moreover, computing technologies provide computational power to many tools and applications used for operations. From the other hand, computing will enable the implementation of new ways of providing services by guaranteeing real-time monitoring and tracking of activities, which are particularly useful for sectors, such as healthcare and transportation. For instance, shipping systems can rely on computing technologies to share

TABLE XIII
AI—TOP EMERGING PRACTICES

Industry	Business Process	Impact macro category	Confidence
Aerospace and Aeronautics	Operations control	Internal	1.00
Agriculture	Operations planning	Internal	1.00
Construction	Product design and development	Internal	1.00
Energy	Market analysis	Internal	1.00
Genera	Buyer–supplier relationships	Internal	1.00
General	Database and data management	Internal	1.00
Healthcare	Database and data management	Internal	1.00
machinery production	Maintenance and diagnostics	Internal	1.00
Manufacturing (general)	Human resources management	Internal	1.00
Passenger transport	Maintenance and diagnostics	Internal	1.00
Steel	Operations control	Internal	1.00
Water	Maintenance and diagnostics	Internal	1.00
Water	Plant services	Internal	1.00
Water	Production of goods	Internal	1.00
Electric power	Maintenance and diagnostics	Internal	0.98
Energy	Operations planning	Internal	0.98
Manufacturing (general)	Maintenance and diagnostics	Internal	0.97
Water	Operations control	Internal	0.97
Construction	Operations control	Internal	0.96
Electric power	Production of goods	Internal	0.96
Energy	Operations control	Internal	0.96
Energy	Plant services	Internal	0.96
Transportation and Logistics	Operations planning	Internal	0.96
Agriculture	Operations control	Internal	0.95
Automotive	Product design and development	Internal	0.94
Manufacturing (general)	Inventory	Internal	0.94
Manufacturing (general)	Quality management	Internal	0.94
Transportation and Logistics	Transportation	Internal	0.94
Construction	Operations planning	Internal	0.93
Electric power	Plant services	Internal	0.93
Electronics	Production of goods	Internal	0.93
Energy	Production of goods	Internal	0.93
Electric power	Operations planning	Internal	0.92
General	Decision making	Internal	0.92
Healthcare	Production of goods	Internal	0.92
Manufacturing (general)	Operations control	Internal	0.92
Manufacturing (general)	Order management - purchasing	Internal	0.92
Manufacturing (general)	Transportation	Internal	0.92
Water	Operations planning	Internal	0.92
Energy	Maintenance and diagnostics	Internal	0.91
Energy	Provision of services	Internal	0.91
Manufacturing (general)	Warehouses	Internal	0.91
Manufacturing (general)	Operations planning	Internal	0.90
Electric power	Operations control	Internal	0.87
Electric power	Provision of services	Internal	0.86
Financial services	Operations control	Internal	0.86
Biomedical	Operations planning	Internal	0.85
Construction	Maintenance and diagnostics	Internal	0.85
Manufacturing (general)	Product design and development	Internal	0.85
Passenger transport	Operations planning	Internal	0.84
Automotive	Product innovation	Internal	0.83
Biomedical	Operations control	Internal	0.83
Electric power	Market analysis	Internal	0.83
Manufacturing (general)	Raw materials management	Internal	0.83
Retail	Inventory	Internal	0.83
Automotive	Operations control	Internal	0.82
Manufacturing (general)	Production of goods	Internal	0.82
Financial services	Credit risk and financial monitoring	Internal	0.81
Construction	Production of goods	Internal	0.80
Passenger transport	Operations control	Internal	0.80
Transportation and Logistics	Operations control	Internal	0.80
Agriculture	Quality management	Internal	0.79
Automotive	Production of goods	Internal	0.78
Electronics	Maintenance and diagnostics	Internal	0.78
Healthcare	Operations planning	Internal	0.76
Healthcare	Provision of services	Internal	0.76
Transportation and Logistics	Maintenance and diagnostics	Internal	0.76
Entertainment	Market analysis	Internal	0.74
Restaurant and café	Market analysis	External	0.73
Transportation and Logistics	Delivery	Internal	0.72
Digital	Provision of services	External	0.70
Healthcare	Operations control	Internal	0.69
Software	Provision of services	Internal	0.67
Financial services	Provision of services	Internal	0.65
Passenger transport	Provision of services	Internal	0.65
Services (general)	Market analysis	External	0.65
Hotels and accommodation	Market analysis	External	0.61
Agriculture	Production of goods	Internal	0.59
Tourism	Market analysis	External	0.59
Financial services	Market analysis	External	0.58
Fashion	Market analysis	Internal	0.55
Passenger transport	Market analysis	Internal	0.55
E-commerce	Market analysis	External	0.53
Retail	Market analysis	Internal	0.52

TABLE XIV
BLOCKCHAIN—TOP EMERGING PRACTICES

Industry	Business Process	Impact macro category	Confidence
Automotive	Supplier payment	Internal	1.00
Construction	Buyer–supplier relationships	Internal	1.00
Electric power	Provision of services	Internal	1.00
Electric power	Sales and sales channels	Internal	1.00
Electric power	Supplier payment	Internal	1.00
Energy	Financial transactions	Internal	1.00
Food and Beverage	Order management - purchasing	Internal	1.00
General	3PL 4PL Couriers - Outsourcing	Internal	1.00
Manufacturing (general)	Operations control	Internal	1.00
Manufacturing (general)	Transportation	Internal	1.00
Transportation and Logistics	Financial transactions	Internal	1.00
Transportation and Logistics	Transportation	Internal	0.96
Food and Beverage	Distributors and wholesalers	Internal	0.93
General	Buyer–supplier relationships	Internal	0.92
General	Database and data management	Internal	0.92
Transportation and Logistics	Delivery	Internal	0.92
Financial services	Financial transactions	Internal	0.91
Manufacturing (general)	Buyer-supplier relationships	Internal	0.90
Manufacturing (general)	Order management - purchasing	Internal	0.90
Healthcare	Database and data management	Internal	0.88
Healthcare	Provision of services	Internal	0.88
Manufacturing (general)	Production of goods	Internal	0.88
Transportation and Logistics	3PL 4PL Couriers - Outsourcing	Internal	0.87
Manufacturing (general)	Database and data management	Internal	0.86
General	Accounting and auditing	Internal	0.85
Transportation and Logistics	Operations control	Internal	0.85
Food and Beverage	Quality management	External	0.82
General	Financial transactions	Internal	0.81
Financial services	Provision of services	Internal	0.79
Agriculture	Database and data management	Internal	0.68
Food and Beverage	Buyer–supplier relationships	Internal	0.67

TABLE XV
COMPUTING—TOP EMERGING PRACTICES

Industry	Business Process	Impact macro category	Confidence
Manufacturing (general)	Operations planning	Internal	1.00
Transportation and Logistics	Delivery	Internal	0.96
Manufacturing (general)	Maintenance and diagnostics	Internal	0.95
Food and Beverage	Operations control	Internal	0.93
Construction	Operations control	Internal	0.92
Food and Beverage	Buyer–supplier relationships	Internal	0.91
General	Database and data management	Internal	0.91
Passenger transport	Operations control	Internal	0.91
Manufacturing (general)	Operations control	Internal	0.89
Transportation and Logistics	Transportation	Internal	0.89
Digital	Provision of services	Internal	0.87
Healthcare	Provision of services	Internal	0.86
Manufacturing (general)	Production of goods	Internal	0.81
Electric power	Operations control	Internal	0.80
Healthcare	Database and data management	Internal	0.79
Healthcare	Operations control	Internal	0.70
Healthcare	Operations planning	Internal	0.70

information about the shipment with the customer as well as to calculate the delivery time. The computational power of computing technologies allows the effective management of resources, providing support to the calculation of routes and the scheduling of the transport system.

Digital applications are the category exhibiting the higher number of emerging practices affecting external performance (see Table XVI). In particular, chatbots, web applications, apps, and social networks will provide support to clients and guarantee real-time services with higher service levels. Chatbots handle customer queries in a timely and correct manner, improving the customer experience and helping clients connect to the brand as well as they optimize customer decision-making performance. Moreover, they also collect information about clients, useful to customize the product offer and understand market needs. Social media solutions are fundamental to implement a two-way symmetrical and interactive communication with customers, increasing customer experience, reducing negative feedback, and providing opportunities to foster stronger relationships. Digital applications are also useful for enhancing internal performance

TABLE XVI
DIGITAL APPLICATIONS—TOP EMERGING PRACTICES

Industry	Business Process	Impact macro category	Confidence
Manufacturing (general)	Operations planning	Internal	1.00
Transportation and Logistics	Delivery	Internal	0.96
Manufacturing (general)	Maintenance and diagnostics	Internal	0.95
Food and Beverage	Operations control	Internal	0.93
Construction	Operations control	Internal	0.92
Food and Beverage	Buyer–supplier relationships	Internal	0.91
General	Database and data management	Internal	0.91
Passenger transport	Operations control	Internal	0.91
Manufacturing (general)	Operations control	Internal	0.89
Transportation and Logistics	Transportation	Internal	0.89
Digital	Provision of services	Internal	0.87
Healthcare	Provision of services	Internal	0.86
Manufacturing (general)	Production of goods	Internal	0.81
Electric power	Operations control	Internal	0.80
Healthcare	Database and data management	Internal	0.79
Healthcare	Operations control	Internal	0.70
Healthcare	Operations planning	Internal	0.70

TABLE XVII
GEOSPATIAL TECHNOLOGIES—TOP EMERGING PRACTICES

Industry	Business Process	Impact macro category	Confidence
Construction	Operations planning	Internal	1.00
Construction	Strategic planning	Internal	1.00
General	3PL 4PL Couriers - Outsourcing	Internal	1.00
General	Buyer–supplier relationships	Internal	1.00
Transportation and Logistics	Transportation	Internal	1.00
Electric power	Operations planning	Internal	0.95
Agriculture	Operations planning	Internal	0.93
Agriculture	Production of goods	Internal	0.92
Water	Operations planning	Internal	0.92
Agriculture	Strategic planning	Internal	0.91
Construction	Operations control	Internal	0.91
Energy	Operations planning	Internal	0.91
Agriculture	Operations control	Internal	0.90
Electric power	Strategic planning	Internal	0.89
Energy	Strategic planning	Internal	0.86
Water	Operations control	Internal	0.77
Passenger transport	Provision of services	Internal	0.68
Transportation and Logistics	Delivery	Internal	0.67
Transportation and Logistics	Operations control	Internal	0.59
Tourism	Market analysis	Internal	0.50

since they will support internal operations by providing instruments and tools for employees. In addition, robotic process automation helps organizations to save costs of operations by no longer having to rely on customers or to outsource tasks. They can also be considered as an instrument to optimize supply chains since they provide a common language to supply-chain members, e.g., by implementing application programming interfaces (APIs) and webservices to share information and manage supply-chain relationships.

Geospatial technologies could enhance internal performance by providing information to support decision making in planning and management of some services (see Table XVII). They find interesting applications in public utilities, such as electric power, energy, and water. Geospatial technologies are used to find the optimal location of storage centers—mapping and checking the features of the surrounding areas, to plan local, regional, and national resource capacity and distribution, and collect data for the effective resource management and supply. Additionally, they probably represent the most promising key technology to enhance business performance in the primary sector. For instance, geospatial technologies allow field mapping, crop phase monitoring, disease management, yield estimation, soil mapping, weed mapping, and hotspot for disease incidence. Applications of geospatial technologies cover not only strategic planning and operations management but also distribution logistics. They provide information to transportation planning applications to optimize routes, monitor hijacking, improve fuel and time efficiencies, and monitor driver behavior.

The main opportunities of exploiting immersive environments are twofold (see Table XVIII). First, they are useful to improve internal performance in the manufacturing sector, with a focus on operations, R&D, and distribution. For instance, warehouse management can be beneficial of augmented reality through the use of smart glasses to help operators with order picking. Digital twin will revolutionize various operations' processes, such as maintenance and diagnostics, since it possesses data from the physical entity and employs it to build a digital model useful for anomaly detection, fault diagnosis, predictive maintenance,

TABLE XVIII
IMMERSIVE ENVIRONMENTS—TOP EMERGING PRACTICES

Industry	Business Process	Impact macro category	Confidence
E-commerce	Sales and sales channels	External	1.00
Manufacturing (general)	Warehouses	Internal	1.00
Manufacturing (general)	Work health and safety	Internal	1.00
Retail	Customer service	External	1.00
Manufacturing (general)	Operations control	Internal	0.98
Manufacturing (general)	Maintenance and diagnostics	Internal	0.97
Manufacturing (general)	Operations planning	Internal	0.97
Manufacturing (general)	Production of goods	Internal	0.96
Manufacturing (general)	Quality management	Internal	0.94
Manufacturing (general)	Product design and development	Internal	0.93
Education	Training–education–organizational culture	Internal	0.91
Retail	Sales and sales channels	External	0.91
Tourism	Provision of services	External	0.86
Fashion	Customer service	External	0.82
Healthcare	Provision of services	Internal	0.72

TABLE XIX
IOT—TOP EMERGING PRACTICES

Industry	Business Process	Impact macro category	Confidence
Electric power	Maintenance and diagnostics	Internal	1.00
Manufacturing (general)	Human resources management	Internal	1.00
Manufacturing (general)	Operations planning	Internal	1.00
Manufacturing (general)	Transportation	Internal	1.00
Manufacturing (general)	Warehouses	Internal	1.00
Manufacturing (general)	Maintenance and diagnostics	Internal	0.97
Transportation and Logistics	Transportation	Internal	0.95
Food and Beverage	Buyer–supplier relationships	Internal	0.94
Agriculture	Production of goods	Internal	0.92
Food and Beverage	Operations control	Internal	0.92
Construction	Operations control	Internal	0.88
Manufacturing (general)	Buyer–supplier relationships	Internal	0.88
Manufacturing (general)	Operations control	Internal	0.88
Transportation and Logistics	Operations control	Internal	0.86
GENERAL	Database and data management	Internal	0.85
Manufacturing (general)	Production of goods	Internal	0.85
Agriculture	Operations control	Internal	0.84
Transportation and Logistics	Delivery	Internal	0.84
Food and Beverage	Inventory	Internal	0.79
Electric power	Operations control	Internal	0.78
Manufacturing (general)	Inventory	Internal	0.78
Healthcare	Operations planning	Internal	0.70
Healthcare	Provision of services	Internal	0.67
Healthcare	Operations control	Internal	0.64

performance analysis, and production quality prediction. Second, immersive environments are promising technologies for marketing, e.g., to show virtual catalogues or presentation of products. During COVID-19 emergency, they are also replacing traditional communication channels and supporting revenues. Indeed, the external performance can be improved by employing them to build a new sale channel to sell products or provide services, e.g., through virtual rooms to try products or virtual tours in locations and museums. Moreover, immersive environments, such as augmented and virtual reality, support customer satisfaction.

IoT is fundamental for collecting information necessary to monitor and control processes as well as for transferring and sharing information (see Table XIX). In SCM, it is used to improve the relationship with both upstream and downstream partners. For instance, for a better management of procurement activities, IoT digitalizes activities and helps real-time monitoring of partners. IoT allows the monitoring of pallets in real time from the factory to the distribution center, from warehouse to warehouse, and during transit and storage. For the manufacturing sector, it has also consolidated applications in operations management, enhancing internal performance. Indeed, it allows machines to communicate with each other and to implement smart production with networking and remote technologies, such as fault diagnosis, monitoring of operations, and transmission of information and instructions to other machines, supply-chain members, and employees. However, stable emerging practices have been found for specific sectors. In the agriculture one, IoT solutions collect data on plantations to support crop monitoring, disease prevention, and irrigation control. In the electric power industry, sensors are installed to monitor the health status of the network and collect information useful to predict future failures and outages that may occur in the distribution lines.

Open and crowd-based platforms have three main categories of frequent applications (see Table XX). First, the use of open

TABLE XX
OPEN AND CROWD-BASED PLATFORMS—TOP EMERGING PRACTICES

Industry	Business Process	Impact macro category	Confidence
Digital	Database and data management	Internal	1.00
Retail	Delivery	Internal	0.89
E-commerce	Delivery	Internal	0.84
Transportation and Logistics	Delivery	Internal	0.84
Manufacturing (general)	Product design and development	Internal	0.80
Healthcare	Provision of services	Internal	0.79

TABLE XXI
PROXIMITY TECHNOLOGIES—TOP EMERGING PRACTICES

Industry	Business Process	Impact macro category	Confidence
Construction	Operations control	Internal	1.00
Manufacturing (general)	Human resources management	Internal	1.00
Retail	Market analysis	External	1.00
Transportation and Logistics	Delivery	Internal	1.00
Manufacturing (general)	Inventory	Internal	0.95
Transportation and Logistics	Transportation	Internal	0.92
Manufacturing (general)	Operations planning	Internal	0.91
Manufacturing (general)	Warehouses	Internal	0.90
Retail	Customer service	External	0.85
Retail	Inventory	Internal	0.84
Manufacturing (general)	Operations control	Internal	0.83
Food and Beverage	Buyer–supplier relationships	Internal	0.82
Transportation and Logistics	Operations control	Internal	0.80
Food and Beverage	Quality management	External	0.64
Healthcare	Operations control	Internal	0.64

data, open access, and open source allows access to important information and applications to support processes, such as the optimization of the services provided in the healthcare industry. Second, open innovation and crowdsourcing platforms support innovation, knowledge, and technology management in the manufacturing sector. Firms can create open spaces to present R&D challenges to a crowd of solvers, develop and find creative solutions to established problems, as well as engage a crowd in the early stages of innovation and product development processes. Third, the implementation of crowdsourcing and crowdshipping platforms, in particular referring to delivery and logistics' services, provides advantages in terms of internal performance. Indeed, crowdsourcing delivery can be useful to dramatically shorten delivery times and minimize last mile delivery costs. Specific platforms can be implemented to create match between parcel delivery tasks and ad-hoc drivers, mainly by implementing algorithms for automatic association and definition of optimized delivery routes.

Proximity technologies allow real-time monitoring of inventories and operations (see Table XXI). In the transportation and logistics industry, it is possible to track and trace the movement of products in a supply chain and control the entire transportation process in order to reduce the loading, unloading, and transportation time, find counterfeits and identifying inconsistencies. In the manufacturing sector, it is used to optimize warehousing activities and managing inventories. Moreover, by using biometrics, it is possible to track employees, authenticate and verify the identity, understand behaviors, and check their performance. In the retail industry, improvements in terms of external performance can be achieved by implementing proximity technologies, such as eye tracking and radio-frequency identification (RFID), to study clients and customer decision making and provide personalized assistance during the purchase and information about the availability of products. In the food and beverage industry, information acquired by proximity technologies is used to improve the safety and the quality of the food since captured data can be shared and published in a traceability system. Clients can scan a QR code and access to information about product, process, provenance, and company information.

Robotics can be implemented in many business processes and industries (see Table XXII). The potential implementation of drones, autonomous vehicles, and other technologies included into robotics will improve the performance of warehouse, transportation, and delivery activities. As to last mile delivery, new organizational models can be implemented, with many opportunities of optimizing time, cost, and quality of the service. Regarding the manufacturing sector, the opportunity of implementing robotics to replace/support the human being or implement automation is the main opportunity of internal performance enhancement. However, robotics' technologies also find stable applications for the management of operations in industries belonging to the tertiary sector, such as healthcare, hotels and accommodation, restaurant and café, and retail. In particular, service robots have proved their usefulness in robotic-assisted surgery and support to patients, as well as to perform front-of-house operations (information provision, service delivery, check-in, and check-out) and back-of-house operations (cleaning, disinfection, and vacuuming the floor).

V. DISCUSSION

A. Theoretical Contribution

The research confirms the power of key technologies in increasing business performance and their significant role in unlocking new practical applications and emerging practices. Despite the risks in implementing emerging practices, firms

TABLE XXII
ROBOTICS—TOP EMERGING PRACTICES

Industry	Business Process	Impact macro category	Confidence
E-commerce	Warehouses	Internal	1.00
Healthcare	Work health and safety	Internal	1.00
Manufacturing (general)	Maintenance and diagnostics	Internal	1.00
Manufacturing (general)	Operations control	Internal	1.00
Manufacturing (general)	Quality management	Internal	1.00
Manufacturing (general)	Production of goods	Internal	0.96
General	Delivery	Internal	0.95
Manufacturing (general)	Warehouses	Internal	0.95
Agriculture	Operations control	Internal	0.92
Manufacturing (general)	Product design and development	Internal	0.91
Retail	Warehouses	Internal	0.88
Transportation and Logistics	Transportation	Internal	0.85
Healthcare	Delivery	Internal	0.84
Passenger transport	Operations control	Internal	0.84
Transportation and Logistics	Delivery	Internal	0.80
E-commerce	Delivery	Internal	0.79
Automotive	Production of goods	Internal	0.78
Healthcare	Operations control	Internal	0.78
Healthcare	Provision of services	Internal	0.78
Passenger transport	Provision of services	Internal	0.71
Hotels and accommodation	Provision of services	Internal	0.67
Retail	Delivery	Internal	0.62
Restaurant and café	Delivery	Internal	0.55

and early adopters can limit such risks by selecting those that fit with the belonging industry, the business function/process, and the specific needs of performance improvement. From the combination of the variables, it emerges that less than 1% of possible tuples has been detected from the systematic literature review. After the theoretical point of view, this suggests that research could explore a multitude of additional possible combinations in order to test the usefulness of key technologies in other business contexts. Considering all industries, business functions, and business processes, the research demonstrates that key technologies are available for many contexts, sometimes neglected by both scientific research and companies. Therefore, improvements in performance can be reached not only within primary business functions but also within secondary ones. For instance, human resource management, strategic planning, and financial processes can be supported by key technologies. Moreover, there is space for implementing technologies in all industries and not only in the manufacturing ones, underscoring the pervasive role of the Industry 4.0 paradigm. In particular, the tertiary industry reports a significant number of available emerging practices as well as interesting opportunities have been uncovered also for the primary. However, research confirms that the main advancements are present in industries, such as manufacturing, healthcare, and transportation and logistics.

Furthermore, from the analysis of results, the type of impact that predominantly can be achieved by implementing emerging practices is internal performance enhancement. This means that, at the current stage of technical evolution, key technologies are predominantly implemented to improve the performance of internal processes. This means that technologies are primarily seen as an opportunity to change internal activities and enhance internal performance, while the implications for external performance are secondary. Probably, when a key technology switches to a further stage of evolution, and people and society exhibit interest in it, this acknowledgement drives companies in trying to exploit it also to achieve market advantages.

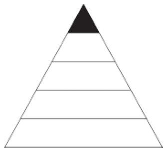
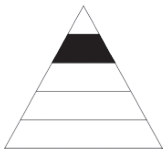
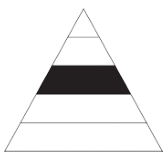
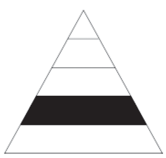
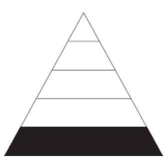
An additional theoretical contribution regards the suggested taxonomy of 11 key technologies. Indeed, the classification derives from the analysis of thousands of scientific articles; therefore, it is robust and exhibits specific peculiarities of each key technology. Such a taxonomy could be the starting point for other research articles aiming at investigating key technologies. To our knowledge, no previous contribution analyzing thousands of scientific papers is found in the literature. Such a classification is not in contrast with other taxonomies suggested by the literature [4], [8] but can be considered more exhaustive, also in terms of number of categories of key technologies.

Moreover, the research confirms the usefulness of scientific papers in order to portray the state-of-the-art of technology development and suggests the implementation of key technologies and emerging practices, underscoring the peculiarities of each technology [15], [92], [104]. The methodology demonstrates that scientific literature can be used as a source of useful information to build a repository of emerging practices. By employing the suggested framework, it is possible to study the evolution of a key technology and understand whether it can be used only within specific industries and business functions/processes or it has general usefulness.

B. Methodological Contribution

The framework for investigating key technologies and emerging practices is the main contribution of this research. It is an original framework supporting researchers and companies in building a repository of emerging practices. The methodology proposed to perform a systematic literature review allows users to extract information from scientific research to study the evolution of the implementation of key technologies in all business contexts. Each practice is associated with a series of standardized variables—key technology, industry, business function, business process, and impact—in order to allow a firm to filter and detect the list of the best promising practices that

TABLE XXIII
EXAMPLE OF IMPLEMENTATION WITHIN THE FOOD AND BEVERAGE INDUSTRY

Level	Description	Comments	Example
	Industry	Selection of the belonging industry in order to find emerging practices that fit with the potential context of application. It is also possible to find "horizontal" practices that can be used in all businesses.	1. Industry: Food & Beverage
	Impact	Definition of the expected outcome that the firm intends to achieve by implementing the key technology. Impacts refer to various elements of performance, such as internal or external.	1. Industry: Food and Beverage 2. Impact: Costs reduction
	Business function/process	Identification of the business function/process where the company plans to implement the key technology. It is likely that the decision maker should allocate the new technological resources to specific business areas and units.	1. Industry: Food and Beverage 2. Impact: Costs reduction 3. Business function: Distribution
	Key technology	Detection of key technologies from whose implementation it is possible to obtain the desired impact. Key technologies are classified in 11 categories, therefore with this step the list of useful categories is displayed, and the user can select one of them.	1. Industry: Food and Beverage 2. Impact: Costs reduction 3. Business function: Distribution 4. Key technology: IoT
	Emerging practice	Listing of emerging practices employing the selected technology. Each emerging practice is a practical application of the key technology. A description is reported, clarifying usefulness, aim, implementation and peculiarities of the focal practice. Activities supported operations and data employed are better clarified. The difference between best and standard practices is underscored.	"Use of sensors capable of monitoring sensitive data along the food supply chain and collecting information about the integrity of food products to share with distribution partners. It allows companies to avoid costs due to food recalls."

fit with the objectives of business performance enhancement. Compared with other repositories, it is a larger dataset, which can be continuously updated, being scientific literature the source of information. For instance, the actual version of the SCOR model, which is one of the most acknowledged frameworks that collects business practices, is four years old, which is a time interval not compatible with the concept of emerging practice. Moreover, the number of emerging practices is significantly higher, not comparable with other research projects [4], [8]. It is also useful to underscore that each practice is associated with a scientific paper; therefore, it is possible to further study in depth the document to capture additional information useful for the implementation of the emerging practice. The use of scientific literature as a source to capture emerging practices implies a significant research activity to update the repository but guarantees the opportunity to record pioneering and radical opportunities of adoption of key technologies [105].

C. Practical and Managerial Implications

The suggested framework could be the basis for the implementation of a practical tool that firms could employ to make decisions about the adoption of emerging practices and carry out "early adopter" strategies in line with the perspective of Industry 4.0. Indeed, firms, researchers, and business analysts could replicate the methodology to build a repository of emerging business practices that can be directly accessed by stakeholders. It could be possible to perform specific queries to filter practices by industry, business function, business process or impact on the business performance, and obtain a list of emerging practices that fit with the desired outcome.

As follows, an example of how it is possible to transform the methodology into a practical instrument is provided. It is possible for a firm to access a list of emerging practices by considering five steps of filtering in order to select the specific practical application that totally fits with the business. At the first step, it is necessary to define the belonging *industry* of the focal firm so that only emerging practices in line with the field of application will be considered. A second step requires the identification of the desired outcome (*impact*) that the focal company intends to achieve. Indeed, the specific performance need "pushes" toward the selection of technologies that are potentially capable of supporting the achievement of the result. Moreover, the decision maker defines the *business function* as well as the *business process*, where it intends to carry out the new practices. Then, the potential technologies that should be implemented are reported so that it is possible to select the preferred *key technology*. Finally, a list of *emerging practices* that employ the focal technology, fitting with the belonging industry, the desired outcome, and the selected business function/process can be obtained. Each practice represents an opportunity of employing the key technology, i.e., the availability of an application of key technology that, once implemented, is likely to improve the business performance. Since the repository will report only proven practical applications of key technologies, the procedure could lead the user toward the selection of uncommon practices that have the potential of departing from common processes, providing competitive advantage or significant cost savings, with more restricted and reduced risks of adoption. The suggested procedure is particularly flexible, and it is possible to customize the steps of filtering according to the desired logic of implementation. For instance, "technology push" approaches should suggest placing the selection of key technologies before the labels impact and business function/process so that once selected the desired technology to implement, the firm should understand which is its potential impact. Table XXIII provides an example of implementation within the food and beverage industry: a firm aiming at reducing distribution costs will detect the opportunity of using IoT. In particular, a practice employing sensors to monitor the integrity of products is suggested.

Since the repository reports only proven practical applications of key technologies, the framework leads the user toward the selection of uncommon practices that have the potential of departing from common processes, providing competitive advantage or significant cost savings. This will reduce risks and uncertainties associated with the adoption of key technologies within the organization since each practice is associated with a scientific paper where information about the context of implementation of the practice is appropriately described. Therefore, by finding similarities between the case study and the real context of the firm, the riskiness of the investment can be confined within a more acceptable limit.

VI. Conclusion

The aim of the research is to present a framework for performing a systematic literature review aiming at supporting the adoption of key technologies and suggesting emerging practices that fit with the firm's context of application, also considering belonging industry, business function and business process, where to implement the technology, and the desired business impact. Having recorded thousands of emerging practices, it was possible to perform an analysis on the 11 categories of key technologies. Results show interesting insights regarding the use of key technologies and the relationship with business performance. Since emerging practices are gathered from scientific papers, results can be considered as a valid basis to suggest future implementation of key technologies and the adoption of those emerging practices that are the most interesting and candidate to become future best practices.

In this article, it was necessary to underscore some limitations that were a consequence of the dataset employed for the research. Emerging practices were detected from the analysis of a sample of scientific papers published from January 2019 to July 2022, while many other documents were available in the literature, also considering other sources not included in this research. The research was limited to papers where specific words were reported in title or abstract. It cannot be excluded that other scientific contributions could be useful for the enrichment of the repository. Moreover, despite the use of standardized labels, the researchers provided a personal interpretation of the content of a paper; therefore, it cannot be excluded that there may be errors in the registration of practices, albeit to a limited extent. Additionally, scientific papers cannot exhaustively consider all possible applications of key technologies, which could not be recorded within the repository. For instance, some emerging practices could have been adopted by companies and industries but have not been captured by scientific research. Furthermore, the suggested impacts in terms of external and internal performance also depend on the features of the firm that implements the technology, i.e., structural, organizational, and management issues. Moreover, even though the repository collects worldwide applications of key technologies, the framework does not consider country-level variables. The digital maturity and the infrastructures of a country could affect the likelihood of achieving the expected outcomes. Therefore, the framework aims only at suggesting potential opportunities for business improvements, but the real impact could be reached also depending on other internal and external factors.

Future research will be addressed in implementing other statistical instruments and machine learning techniques to analyze the repository, such as clustering tools and decision trees. Furthermore, since some practices employ more than one key technology at a time, it is interesting to study the co-occurrence of key technologies in order to capture information about the impact of conjunct implementations and the deriving synergies.

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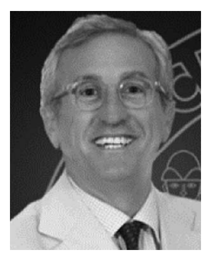

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