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Machine Intelligence and Autonomous Robotic Technologies in the Corporate Context of SMEs: Deep Learning and Virtual Simulation Algorithms, Cyber-Physical Production Networks, and Industry 4.0-Based Manufacturing Systems

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Abstract: This study examines Industry 4.0-based technologies, focusing on the barriers to their implementation in European small- and medium-sized enterprises (SMEs). The purpose of this research was to determine the most significant obstacles that prevent SMEs from implementing smart manufacturing, as well as to identify the most important components of such an operationalization and to evaluate whether only large businesses have access to technological opportunities given the financial complexities of such an adoption. The study is premised on the notion that, in the setting of cyber-physical production systems, the gap between massive corporations and SMEs may result in significant disadvantages for the latter, leading to their market exclusion by the former. The research aim was achieved by secondary data analysis, where previously gathered data were assessed and analyzed. The need to investigate this topic originates from the fact that SMEs require more research than large corporations, which are typically the focus of mainstream debates. The findings validated Industry 4.0′s critical role in smart process planning provided by deep learning and virtual simulation algorithms, especially for industrial production. The research also discussed the connection options for SMEs as a means of enhancing business efficiency through machine intelligence and autonomous robotic technologies. The interaction between Industry 4.0 and the economic management of organizations is viewed in this study as a possible source of significant added value.

Keywords: industry 4.0; SMEs; digitization; financial barriers; financial resources

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1. Introduction

We are now living in a technologically advanced era. Compared to previous industrial revolutions, both the planet and our way of life are undergoing rapid transformations. In terms of society, education, employment, and notably production, the rate of change is unprecedented. A quick survey of previous industrial revolutions demonstrates how they preceded the current scenario [1]. During the first industrial revolution, the notion of harnessing water and steam for mechanization began to develop. During the second industrial revolution, which began a century later, electric power was utilized for the first time in mass production. In the 1970s, the concept of automation was introduced as a result of the third industrial revolution [2]. After these three turning moments in human history, data-driven technology was implemented and a new reality, known as the fourth industrial revolution, which gave rise to Industry 4.0, was established [3]. As a relatively new concept, this topic may be seen by some as disputed and broad [4]. Due to the uniqueness associated with these transformations, more research is needed, particularly in terms of computation task cooperation, virtual modeling and digital twin machining technologies, and wireless sensor networks throughout automated manufacturing and autonomous robotic systems.

The primary purpose of this study is to identify the most significant barriers to implementing Industry 4.0 in European SMEs. The study also identifies the most crucial ingredient for a successful deployment and investigates whether all organizations have an equal opportunity to adopt Industry 4.0 in the European context, which may be regarded its most significant added value. Moreover, the identification of these barriers is the main research objective, as several authors mostly focus on the identification of strategies and stimulation of Industry 4.0 implementation (e.g., see [5–7]). The research is undertaken under the premise that SMEs and massive corporations have diverse implementation needs in relation to autonomous control systems, intelligent connectivity infrastructures, and virtual machine interoperability. Consequently, rivalry posed by massive corporations may outshine SMEs. Finding a viable solution to such an issue is a major objective of the study. While it is evident that financial resources are required for the implementation of Industry 4.0, we raise the question of whether heterogeneous businesses of varying sizes are equally prepared for the change and have equal access to opportunities. This requires financial resources as well as robust knowledge and awareness of what is required for putting Industry 4.0 technologies into practice by integrating robotic navigation systems, mobile sensors and actuators, and context awareness tools in mobile edge computing environments. During the implementation of data-driven systems based on Industry 4.0, difficulties may occur [8].

The purpose of this study is to determine whether the standard position, that only large businesses can adopt Industry 4.0 because it requires significant financial resources, and the assumption that SMEs will suffer significant disadvantages due to the disparity between large and small businesses in relation to Industry 4.0, is accurate. The classification of companies in line with the standard evaluation of enterprises based on the criteria of the European Union (EU) is explored as it relates to the core issue, since the focus is mostly on European SMEs in connection to the business climate. The conditions for the deployment of Industry 4.0 technologies are explored briefly, along with the upsides and disadvantages of adopting industrial artificial intelligence, context-aware robotic networks, and cyber-physical intelligent manufacturing systems [9]. Moreover, image processing and computational prediction tools, distributed sensing and mobile robot technologies, and visual cognitive and environment mapping algorithms articulate Industry 5.0-driven sustainable technologies, operations, and tasks as regards digital twin-based product development. Cognitive and cloud robotics, machine learning and intelligent control algorithms, and digital twin simulation and predictive geospatial modeling tools shape the Industry 5.0 environment. Our research examines the internal obstacles that SMEs must overcome in order to incorporate big data-driven decision-making processes, computer vision algorithms, and imaging-based navigation technologies. The research analyzes the most relevant obstacles to SMEs implementing Industry 4.0, including a concise comparison of SME adoption of cyber-physical production networks, as well as a discussion of the possible benefits of overcoming SME implementation challenges. The EU's financial support for SMEs in relation to Industry 4.0 is reviewed alongside other potential sources of aid, as the study focuses primarily on European corporations [10]. Based on the present implementation of Industry 4.0, it may appear that only major companies have the resources necessary to configure cyber-physical system-based smart factories, since they can afford considerable financial and operational resources. Potential concerns associated with this topic include unfair competition and severe disadvantages for SMEs compared to large businesses [11].

The paper is divided into the sections listed below. First, this article explains the basic ideas necessary to comprehend Industry 4.0 and gives a summary of its principles in the literature review section. The subsequent section outlines the topic's essential sources and methodologies. Following the preceding section are the outcomes of the SME concentration on barriers and financial assistance. The research ends with a discussion. In conclusion, the most essential elements for a successful adoption of Industry 4.0 are enumerated, along with the greatest obstacles for SMEs.

Key research contributions:

- Machine intelligence and autonomous robotic technologies in the corporate context of SMEs develop on distributed intelligence and real-time data simulation tools, visual perception and situational awareness algorithms, and cyber-physical production systems.
- Industry 4.0-based manufacturing systems integrate sensor and actuator devices, cognitive data visualization and virtual simulation tools, and cloud and swarm robotics.
- Image recognition and remote sensing technologies, signal processing and big data management tools, and virtual manufacturing systems are pivotal in smart robotic environments.
- Sensor data fusion and remote intelligent object detection tools, cognitive decision-making algorithms, and digital twin modeling configure smart manufacturing execution and network robot systems.
- Autonomous visual object detection and sensor data fusion tools, operational process simulation and robot motion control algorithms, and virtual machining systems shape smart manufacturing processes.
- Deep learning and virtual simulation algorithms, data visualization functionalities, and digital twin technologies enable autonomous multi-robot systems in smart factories.
- Object tracking and remote sensing algorithms, mobile autonomous robots, and remote intelligent image detection tools optimize smart process manufacturing and digital twin-based product development.
- Smart connected objects, autonomous robotic and cyber-physical manufacturing systems, and virtual process simulation and machine data mining tools articulate Industry 4.0-based networked environments.

2. Literature Review

Cyber-security configurations, cyber-physical production networks, and smart manufacturing systems are explored in relation to Industry 4.0. Cyber-physical process monitoring systems and environmentally responsible production related to the Internet of Things began with the rapid expansion of digital technology around the turn of the 21st century [1]. Industry 4.0, often known as smart manufacturing or industrial internet, aims to optimize global production capacities in terms of visual and spatial intelligence, simulation modeling and semantic sensor technologies, and mobile autonomous robots [8]. Industry 4.0-based digitization processes related to cyber-physical production networks develop on autonomous cognitive and digital twin systems, robotic swarm operations, and artificial intelligence technologies [9]. Due to a self-organizing cyber-physical production system, mass production becomes more flexible in terms of quantity and may be customized as a result of process mining techniques, and data modeling and simulation tools [10]. The fundamental components of Industry 4.0 [11] are automation, the incorporation of cutting-edge technology into industrial processes, and data exchange, which require the continual connectivity of machines capable of working without human intervention. This implementation necessitates the deployment of intelligent networked cyber-physical systems and of digital twin technology by integrating computer-generated virtual objects, robotic and sensor devices, and contextual data monitoring tools in smart manufacturing enterprises [12]. The primary objective of cyber-physical smart manufacturing systems [13] is to automate every step of this process, from configuration and production through supply chain and predictive maintenance. The goal of integrating Industry 4.0 is to transform industrial manufacturing by harnessing innovative technologies and digitalization according to remote sensing data, machining process monitoring, and interoperable automation systems. Globalization, which increases data-driven competitiveness, necessitates sufficiently agile production to satisfy market needs [14]. This objective may be accomplished by integrating Industry 4.0 technology and autonomous manufacturing systems into organizational value chains and product design processes [15].

To effectively implement Industry 4.0 and digital twin systems, the integration process requires the transformation of industrial facilities into smart factories, where connectivity and interoperability develop on Internet of Things-enabled monitoring and sensor fusion-based systems, predictive modeling tools, and augmented reality algorithms [16]. Industry 4.0 is a socioeconomic phenomenon as well as a technical one, characterized by the utilization of smart manufacturing big data, real-time advanced analytics, and product decision-making information systems [17]. Technological advances enable the interoperability and interconnectivity of Internet of Things-based real-time production logistics characterizing smart manufacturing facilities, which are the central pillar of Industry 4.0 and artificial intelligence-driven big data analytics. The initial stage in the establishment of smart factories [18] was the manufacturing of a single item by employing production lines comprised of equipment with well-defined functions typified by virtual data analytics, cognitive digital twins, and cloud computing algorithms. With continued expansion, more prospects were explored, such as the broad production of a variety of manufactured items developed on modeling and simulation tools, mobile robotic devices, and interactive data visualization technologies. Innovative computer numerical control devices now make flexible manufacturing possible [19]. Manufacturers can adjust the type and amount of their products to meet the demands of a rapidly changing market by harnessing digital twin-based industrial data, resource and production scheduling, and cognitive artificial intelligence across distributed interoperable environments [20]. Cyber-physical production systems, which are the essential elements of smart factories [21], are characterized primarily by decentralization and autonomy, integrating data-driven technologies with physical systems [22]. Cyber-physical production systems deploy Internet of Things-based real-time production logistics and robotic device capabilities across industrial processes [23] in order to transfer and gather factory floor data by use of predictive maintenance and computer vision detection technologies, spatial mapping and reinforcement learning algorithms, and virtual simulation modeling tools. Data-driven Internet of Things systems powered by artificial intelligence technologies cover how cyber-physical systems communicate by integrating autonomous navigation systems, computer vision capabilities, and remote interaction sensors [24]. Enhanced connectivity enables the collection and sharing of real-time data pertaining to all aspects of industrial processes [25].

Cyber-physical production systems are self-governing, with the ability to make decisions based on real-time data and virtual simulation algorithms, inspection of prior actions' outcomes, and learning from by-products [26,27]. Enterprise resource planning applications, cyber-physical production networks, artificial intelligence-based decision-making algorithms, and manufacturing execution systems are software control providers in decentralized smart factories [28]. Permanent Wi-Fi access is necessary for data-driven machine-to-machine interactions on the shop floor. Industrial Internet of Things enables machine interaction and continuous connection by use of virtual simulation algorithms [29], being developed on cyber-physical system-based real-time monitoring, big data-driven decision-making processes, and wireless sensor networks [30]. In smart manufacturing, human-machine interaction is necessary since certain tasks cannot be fully automated [31]. Intelligent factories can produce intelligent items with sensors that aid in localization and life cycle monitoring in addition to manual manufacturing, considerably simplifying maintenance [32]. Product lifetime management is the business operation responsible for managing the manufacturing process in cyber-physical production networks by integrating intelligent decision-support systems, virtual reality mapping tools, and digital twin technologies [33]. Data perception and sharing are pivotal in product lifecycle management throughout smart factories by use of digital twin simulation modeling, sensing and actuating devices, and situational awareness and spatial cognition algorithms towards the Industry 5.0 environment [34] (Table 1).

Table 1. Summarized findings related to deep learning and virtual simulation algorithms, cyber-physical production networks, and Industry 4.0-based manufacturing systems.

• 3D convolutional neural networks, computer vision and path planning algorithms, and intelligent data processing and smart environment modeling tools configure cyber-physical production and virtual manufacturing systems.
• Robotic cooperative behaviors require digital twin-driven product development, enterprise resource planning, and process performance monitoring.
• Big data analytics, artificial neural networks, and virtual twinning techniques enable autonomous manufacturing processes throughout industrial cyber-physical systems.
• Virtual machines necessitate blockchain-based data acquisition, intelligent manufacturing equipment, and robotic communication systems.
• Digital twin simulations, robotic operating systems and agent behaviors, and environment perception sensors configure Internet of Things-based cloud manufacturing.
• Cloud networked and autonomous mobile robots harness digital twin-based monitoring and intuitive decision-making tools, sensing and actuation capabilities, and vision and navigation systems.
• Multiple autonomous mobile robots, deep learning-based image processing and context awareness algorithms, and ambient intelligence and visual analytics tools articulate shop-floor production management.
• Swarm computing and motion control algorithms, visual and spatial intelligence tools, and cloud computing technologies shape autonomous task allocation and production process modeling in digital twin-driven smart manufacturing.
• Digital twin systems harness object perception and virtual shop floor operations, captured image data, and visual modeling and multi-machine cooperation tools.
• Autonomous manufacturing control, industrial wireless sensor networks, and predictive maintenance scheduling tools assist smart manufacturing systems in synthetic simulation environments.
• Spatial data acquisition and context recognition tools, machine perception and simulation modeling technologies, and connected mobile devices assist manufacturing execution and robotic operating systems.
• Smart manufacturing enterprises necessitate signal and image processing tools, product digital twins, and motion sensing capabilities.
• Smart manufacturing systems deploy digital twin modeling and intelligent data processing tools, robotic coordination mechanisms, and cognitive decision-making and augmented reality algorithms.
• Machine vision and cloud computing technologies, spatial data processing and cognitive artificial intelligence tools, and digital twin modeling assist production planning and scheduling in smart manufacturing environments.
• Autonomous robotic and digital twin-enabled industrial systems deploy data processing and context awareness algorithms, edge computing technologies, and modeling and simulation tools across smart manufacturing plants.

Source: Authors' compilation.

Big data analytics and cloud manufacturing are important components of Industry 4.0. In addition to their physical representation, machines operating in smart factories may learn from and interact with their surroundings in real time [35], having a virtual identity that is stored in the cloud. By combining cloud-based systems with cyber-physical systems, it is feasible to provide continuous data exchange with cloud-based data collecting systems [36]. Internet of Things sensor networks, real-time big data analytics, and industrial artificial intelligence collaborate to promote the merging of physical and digital worlds. Data gathering and analysis enable real-time threat identification and decision making by collaborative operation mechanisms [37]. Shop floor manufacturing processes that reduce errors by leveraging data mining and context awareness tools, real-time event analytics, and deep learning-based image classification algorithms may increase production across synthetic simulation environments [38]. The global availability of geographically varied data centers facilitates the development and optimization of productivity in enterprises of varying sizes through fault diagnosis algorithms, visual recognition technologies, and distributed computing networks. [39]. Industry 4.0 includes product decision-making information systems, data-driven real-time analytics, and smart sensor devices across intelligent simulation environments [40]. Image recognition and crowd navigation algorithms, sound recognition systems, and ambient intelligence and predictive simulation tools optimize smart manufacturing machines in immersive 3D and Industry 5.0 environments. Cognitive manufacturing and cooperative multi-robot systems deploy sensor–actuator networks, spatial data analytics, and location identification and natural language processing tools. Autonomous and collaborative robots require spatial data visualization and assembly process planning tools, multisensor fusion and cloud-based digital twin technologies, and motion control and context awareness algorithms throughout augmented operating environments. Plant maintenance scheduling and context recognition tools, machine learning techniques, and fault diagnosis systems shape cloud-networked and collaborative robots.

Additive manufacturing creates physical objects based on digital 3D models [41] by printing successive layers into a three-dimensional structure. The value of additive manufacturing lies in its easy customizability. Prior to mass manufacturing, the aforementioned method was commonly utilized to rapidly prototype products [42], as it was a low-cost alternative for generating high-quality goods in small quantities [43]. Computer-generated data are part of both real-world environments and advanced manufacturing technologies [44]. These data can be rendered into graphics that are integrated into the surroundings of the viewer. Augmented reality assists workers in real-time with hard tasks in a dynamic workplace [45]. Artificial intelligence technologies enable machines and computers to carry out operations similar to those performed by personnel throughout manufacturing processes [46]. Machine intelligence and autonomous robotic technologies employ synthetic knowledge as sensing device and automated simulation modeling capabilities in product development processes [47]. Internet of Things-based robotic systems and automated production operations are essential in articulating deep learning-enabled smart process planning and contextual data monitoring. As different types of robots may be harnessed in various industrial sectors, their production utilization differs in terms of context-aware and autonomous cognitive systems, path planning and object recognition algorithms, and ambient intelligence tools [48]. The capabilities of robotic manufacturing processes are advancing in tandem with industrial automation devices, optimizing smart production planning, logistics network, and task administration [49]. By leveraging cognitive decision-making and virtual simulation algorithms, visual perception and performance prediction tools, and real-time process monitoring, robotized manufacturing systems and data-driven digital twins shape production time and output. Smart manufacturing system and virtual twin modeling tools, cognitive cyber-physical production networks, and robotic coordination mechanisms articulate Industry 4.0. [50].

Heavy robotic arms have a tremendous lifting capability. Nevertheless, human assistance with robotics is still required in numerous areas. Co-bots are robots capable of collaborating with humans without endangering their health. Team-working robots are adaptive and capable of learning new abilities [51]. Humanoid robots provide an alternate method. Employed in large-scale production, autonomous robots function as instruments for improving output quality, expanding production, and saving labor [52]. However, industrial robots are prohibitively expensive, especially for SMEs. Co-bots that are lightweight and simple to program are more accessible to SMEs [53]. In order to secure the connectivity of equipment, commodities, and materials, horizontal and vertical system assimilation of data is required for effective corporate communication. Vertical integration digitalizes automated production processes, Internet of Things-based real-time manufacturing logistics, and product life cycle management. Horizontal digitization refers to the integration of data with significant partners, suppliers, and customers. By integrating vertical and horizontal digitization, a digital ecosystem is created in which data flow supports the appropriate operation [54,55]. The necessity for data-driven enterprises to deploy Industry 4.0 technologies stems from the crucial role of autonomous manufacturing systems in outperforming the competition by leveraging vision and navigation tools, fault diagnosis and object recognition algorithms, and mobile robotic devices. Machine intelligence and autonomous robotic technologies, remote sensing systems, and deep neural networks are pivotal in manufacturing virtualization and simulation across smart interactive environments and on digital twin shop floors [56]. Implementing Industry 4.0 entails all activities and services along the whole value chain, not just a manufacturing shift. Robotic autonomous systems, remote sensing algorithms, and digital twin modeling tools shape virtual manufacturing and product development processes in smart factory environments. Operational process modeling tools, digital twin data, and object recognition algorithms optimize intelligent manufacturing equipment and networked robotic systems [57]. Businesses can embrace Industry 4.0 technologies while utilizing existing resources by integrating networked cloud robotics, geolocation data intelligence, and simulation-based digital twins. Cloud and networked robotics integrate product lifecycle data, real-time process monitoring tools, and digital twin technologies in smart manufacturing management. Real-time sensor data, robot motion planning and virtual data augmentation tools, and digital twin-driven product design algorithms assist cyber-physical production networks and Industry 4.0-based manufacturing systems [58] (Table 2).

Table 2. Comparison chart covering performance measurement data analysis.

• Virtual reality-based data analytics, cognitive decision-making algorithms, and deep convolutional neural networks further industrial control and automation systems.
• Shop floor digital twins deploy real-time operational data, smart connected sensors, and 3D spatio-temporal simulations in virtual manufacturing systems and across collaborative multi-robot environments.
• Big manufacturing data, cyber-physical production systems, and smart interconnected robots are pivotal in Industrial Internet of Things.
• Virtual twin data, smart interconnected and cognitive robotic devices, and machine learning and context awareness algorithms are instrumental in Internet of Things-enabled automation and process manufacturing systems.
• Decentralized data analytics, Internet of Things-based decision support systems, and distributed sensor networks optimize product lifecycle management in smart factories and across collaborative industrial environments.
• Digital twin simulation and real-time remote monitoring tools, wireless sensor technologies, and cognitive data mining algorithms assist smart industrial systems.
• Digital twin technologies leverage simulation analytics, environment perception sensors, and cognitive data fusion techniques in smart manufacturing processes.
• Visual tracking and motion planning algorithms, digital twin technologies, and localization and navigation tools optimize autonomous manufacturing processes on the product assembly shop floor.
• Big data analytical and acoustic environment recognition tools, computer vision and swarm intelligence algorithms, and artificial neural networks configure multi-agent robotic systems in digital twin environments.
• Digital twin-based product development necessitates automated prognostics and diagnostics tools, computer vision techniques, and simulation modeling processes in smart factories.
• Industry 5.0-driven sustainable operations necessitate monitoring and sensing technologies, cloud-based production processes, and virtual mapping and data mining tools.
• Autonomous cyber-physical and robotic operating systems harness industrial wireless sensor networks, interconnected virtual devices, and product lifecycle data.
• Internet of Things-enabled control systems, data mapping and processing tools, and prognostic and diagnostic algorithms articulate manufacturing task management in smart networked environments.
• Sensor data fusion, computer vision algorithms, and process simulation and production scheduling tools further develop autonomous robotic systems and smart manufacturing technologies.
• Wireless sensor networks, space situational awareness and computational intelligence tools, and decision support systems enable product lifecycle monitoring and autonomous mobile robot navigation across smart shop floors.

Source: Authors' compilation.

3. Materials and Methods

In order to establish objectives and make decisions on future advancements in preparation for the implementation of Industry 4.0, a clear understanding of the concept is needed [59]. A corporation's common mode of thought and comprehension merges digital mass production, cyber-physical production networks, and real-time big data analytics [60]. Throughout the shift to Industry 4.0 technologies, businesses place a premium on maintaining efficient production by integrating product manufacturing data across digital twin networks [61]. Given the duration of this process, cyber-physical smart manufacturing and big data-driven technologies [62] necessitate additional expenditures. Deep learning-based computer vision algorithms, event modeling and forecasting tools, and big data-driven decision-making processes are instrumental in product lifecycle management systems. Machine intelligence and digital twin technologies harness situational awareness and remote sensing algorithms, cloud-based cyber-physical systems, and image acquisition devices in Industry 4.0-based networked environments. Production process modeling develops on predictive maintenance tools, remote sensing algorithms, and data fusion technologies. Smart interconnected devices, swarm robotic and machine learning algorithms, and process simulation and scheduling tools articulate smart manufacturing systems and digital twin-based virtual factories.

Smart networked factories are configured by computer-assisted technologies merging cyber-physical production systems and leveraging Internet of Things-based real-time production logistics. In addition to product decision-making information systems, Industry 4.0 integration depends on organizational structure, IT proficiency, and strategic-minded management. This research followed the five stages of digital evolution in firms [63] (see also Figure 1):

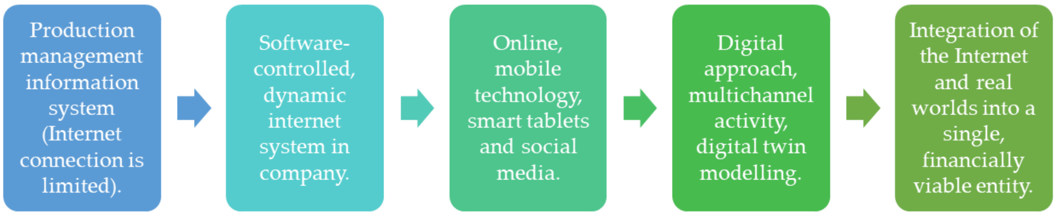


Figure 1. Five phases of digital transformation for businesses. Source: Authors' compilation.

1. The company has a production management information system in place, but its Internet visibility is limited. The organization is starting to think about putting into practice autonomous production processes, Internet of Things sensing networks, and predictive maintenance systems while lacking a coherent digital strategy. It can partially participate in supplier–customer relationship information flows. Simple economic software makes communication with other state administration bodies possible.
2. A company with a software-controlled, dynamic Internet presence begins to recognize the importance of data. Currently, automation and first integration activities are being implemented. Consideration is being given to establishing a digital strategy and engaging in supply and demand chain information flows, including collaborative virtual archives, real-time big data analytics, semi-automatic ordering, etc.
3. The third level consists of the company's utilization of online and mobile technology, smart tablets, and social media. The company has a comprehensive digital strategy and solid data culture foundations, such as initiatives for integrating data culture, real-time absorbed automation, and customized products with virtual components.
4. The next stage may be characterized by the organization's scattered and individualized digital approach, in addition to the multichannel activity that is digitally merged through digital twin modeling. The data architecture is included into each phase of the manufacturing process, including contact with customers and subcontractors, and data exchange. Digital diagnostics forecast system breakdowns and problems.
5. The company is a digitizing platform that integrates the Internet and real worlds into a single, financially viable entity. By utilizing virtual goods that interact with clients throughout their life cycles, it offers customers a unique, personalized experience. The most modern and effective solutions (full automation, real-time sensor networks, 3D printing, etc.) employ a cybernetic system that can independently implement the product's physical component.

After briefly discussing the core components of Industry 4.0, it is essential to address SMEs in order to comprehend their interactions with Industry 4.0 wireless networks, cyber-physical system-based smart factories, and cognitive automation. The fundamental requirement for qualifying SMEs, according to the European Commission, is presented in Table 3 as the number of employees and revenue. These requirements only apply to particular firms [64]. Small firms have fewer than 50 employees and annual sales of up to €10 million, whereas medium-sized enterprises have fewer than 250 employees and an annual revenue of up to €50 million, or more specifically a balance sheet of up to €43 million.

Table 3. Categorization of SMEs.

Company Category	Staff Headcount	Turnover	Balance Sheet Total
Medium-sized	<250	≤€50 m	≤€43 m
Small	<50	≤€10 m	≤€10 m
Micro	<10	≤€2 m	≤€2 m

Source: Authors' compilation.

As indicated in Table 3, the readiness of enterprises for this endeavor may be evaluated on a variety of levels, beginning with strategy and organization, and continuing through smart factories, big data-driven decision-making processes, and manufactured goods to human resources [65].

The formation of the research questions is the first stage in the systematic technique of secondary analysis, which subsequently involves identifying the dataset and thoroughly evaluating it. Thus, the main research problem was clearly stated to identify the most significant barriers of implementing Industry 4.0 in European SMEs. To achieve the main aim of the study, several sources of the secondary data analysis were considered, such as scholarly articles written by experts in a particular field, books and book chapters, conference proceedings, government documents, and annual reports of enterprises.

For the analysis, data from the European Commission, OECD, and Statista were also utilized as well as screening and quality assessment tools (AMSTAR, AXIS, Dedoose, Distiller SR, MMAT, ROBIS, and SRDR). In addition to research on the added value of the non-financial sector, the analyses were based on this topic. The research was also conducted by utilizing secondary data analysis from the SME Alliance. To process the secondary data, the following scientific methods were used (Figure 2): (i) *the method of analysis* that examines a complex research problem by its decomposition into partial sections. In the presented study, the method of analysis was used to investigate the knowledge available in domestic and foreign literature in the mapped research area; (ii) *the method of synthesis*, which is used in processing and synthesizing acquired knowledge; (iii) *the method of comparison*, the result of which is the discovery of a mutual relationship between the researched knowledge, phenomena, or objects, which makes it possible to gain new knowledge about the researched issue; (iv) *the method of exploration* used to better understand the existing problem. In this study, this method was used in the interpretation of the outputs of the performed analyses; (v) *the method of explanation* is aimed at deriving theoretical conclusions from the examined knowledge, which is organized into logical contexts and causal dependencies, which is the basis for the creation of theoretical conclusions about the research problem [66]. The inquiry also included comparative analysis. A total of 56.5% of German businesses are not entirely compliant with Industry 4.0 deployment criteria, according to a survey of 268 businesses [18]. A total of 20% of respondents were only somewhat prepared for the beginner level 1 implementation method. Only 0.3% were regarded as exceptional, attaining level 5 implementation across all criteria (Table 4).

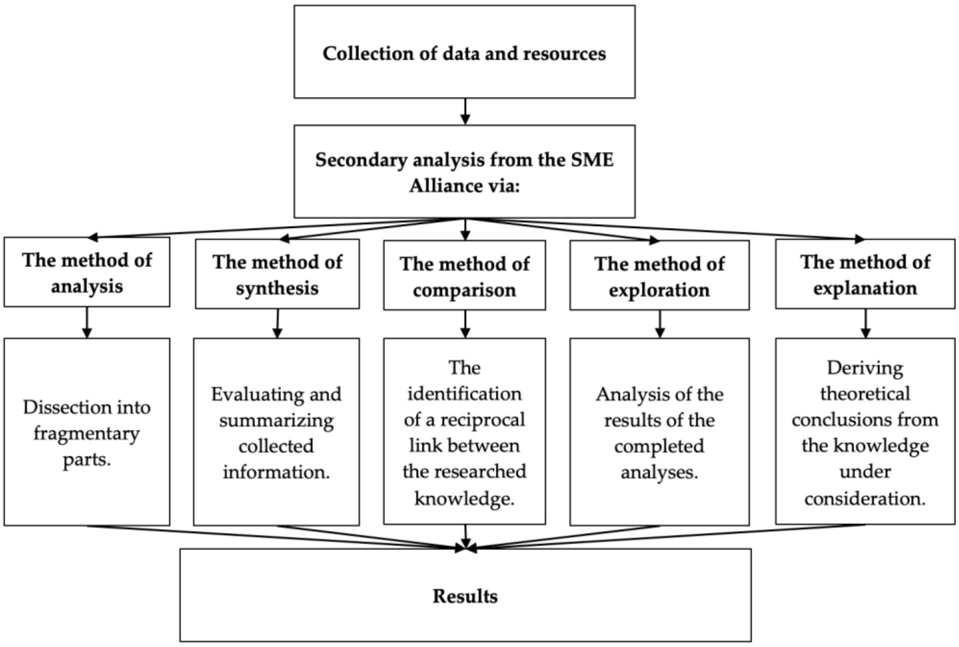


Figure 2. Diagram illustrating the approach used in this study. Source: Authors' compilation.

Table 4. Levels of implementation.

Level	Designation
0	Outsider
1	Beginner
2	Intermediate
3	Experienced
4	Expert
5	Top Performer

Source: Authors' compilation according to [18].

A survey was conducted to determine how prepared businesses were for Industry 4.0. A total of 1500 C-level executives (CXOs) from 19 countries participated. Only 14% of respondents stated they were "extremely confident" in their capacity to solve Industry 4.0′s challenges, while 20% of CXOs indicated their organizations were prepared for an innovative business model. Only 25% of respondents believed their employees had the necessary knowledge to fully integrate Industry 4.0, and 84% were attempting to educate their employees while acknowledging the need for fundamental changes. Fewer than 15% of respondents felt appropriately prepared for autonomous and intelligent technologies [67].

Figure 3 depicts the number of SMEs in the EU during a 15-year period. One can witness a growing number of these firms. In 2022, their population reached around 23 million. SMEs should begin by digitizing their marketing and administrative tasks. For many businesses, the initial step presents the greatest challenge. Once an initial transition to digital technologies has been made, strong technological complementarities can stimulate further acceptance. In order to take this step, and as they identify and embrace further digital technologies, SMEs frequently rely on external systems, support, and advice. This is partially to compensate for a lack of internal capacity, but also for economic reasons. For instance, digital platforms (e.g., social networks and e-commerce marketplaces) offer a substantial opportunity to optimize specific activities at minimal expense (e.g., business intelligence and data analytics services). Similarly, SMEs rely on external consultants or the security-by-design aspects of the digital products and services they employ to manage digital security concerns. In addition, they obtain artificial intelligence (AI) solutions from knowledge marketplaces and can leapfrog to new AI systems using software as a service based on cloud computing. Mobile autonomous robots integrate real-time monitoring and smart manufacturing technologies, cloud computing machines, and image recognition processes. Digital twin-driven smart manufacturing integrates immersive virtual reality simulations, imaging and sensing tools, and data analytics technologies. Collaborative autonomous systems leverage image acquisition and processing tools, mobile robotic devices, and cloud computing analytics in smart manufacturing environments.

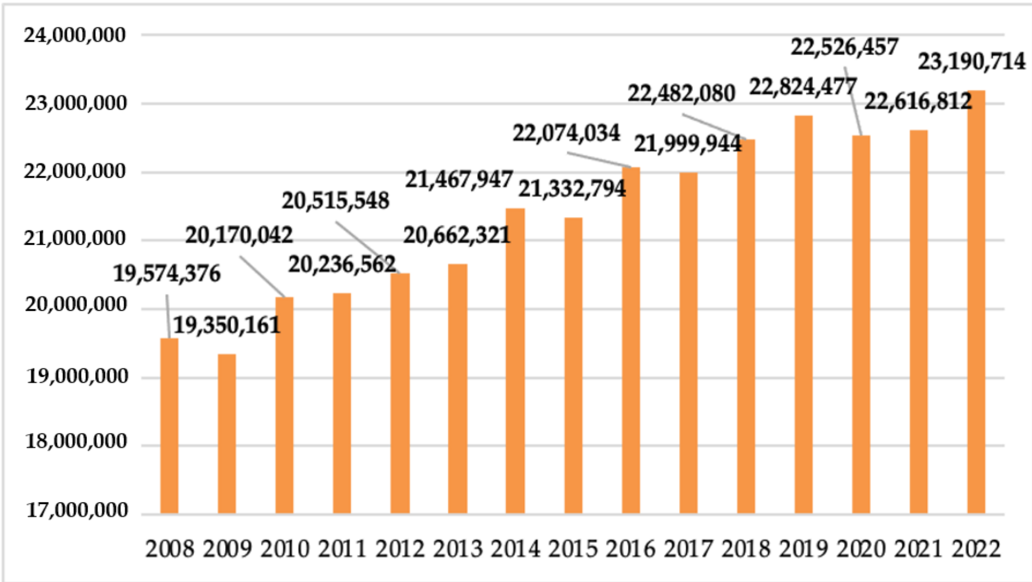


Figure 3. Number of SMEs in the European Union (EU27) from 2008 to 2022. Source: Authors' compilation.

However, technology complementarities can also exacerbate digital disparities, since larger and more digitally aware businesses can more easily adopt more advanced digital practices. Therefore, the chasm between SMEs and larger businesses is particularly obvious in the adoption of more advanced technologies (e.g., data analytics) or when implementation scale is crucial (e.g., enterprise resource planning for back-office integration, and supply-chain and customer relationship management software for front office and production process integration). Digital twin technology, cloud manufacturing processes, and virtual reality modeling tools are pivotal in industrial product lifecycle management. Cyber-physical production and autonomous manufacturing systems integrate sensor fusion capabilities, robotic navigation processes, and smart process planning. Condition monitoring data, plant equipment diagnosis, and digital twin capabilities are pivotal in autonomous production and virtual manufacturing systems. Real-time data visualization and cognitive artificial intelligence tools, virtual equipment and robotic cooperation systems, and predictive modeling and deep learning algorithms are instrumental in visual simulation environments. Networked robots, machine data fusion, and predictive analytics algorithms articulate digital twin-based intelligent manufacturing in the Industrial Metaverse.

The digital shift begins for the majority of SMEs in general administration or marketing functions, where the digital gap between SMEs and larger enterprises in online interactions with the government, electronic invoicing, social media use, and e-commerce is lower. Sensory data acquisition and deep reinforcement learning tools, autonomous robotic and digital twin technologies, and computer vision and predictive maintenance algorithms shape machining process performance. Digital twin-driven smart manufacturing develops on sensor-based data analysis, object recognition processes, and mobile context awareness systems. Virtual machine and ambient intelligence tools, obstacle detection and immersive visualization technologies, and computational prediction and image enhancement algorithms are instrumental in synthetic simulation environments. Smart production systems leverage granular manufacturing data, computation-enabled robotic devices, and simulation and scheduling tools across digital twin shop floors. Digital twin and cloud computing technologies, navigation management tools, and convolutional neural networks further autonomous swarm robots in smart manufacturing environments. Sensing and computing technologies, autonomous visual object detection tools, and mobile robotic systems enable reconfigurable manufacturing processes.

Before implementation obstacles can be evaluated, the advantages and disadvantages of Industry 4.0 technologies must be taken into account. It is vital to properly describe and characterize the implementation inconsistencies of Industry 4.0. There are unquestionably challenges and barriers that must be overcome in order to fully enjoy the benefits of big data-driven technologies, but utilizing industrial artificial intelligence shapes production capacities and productivity, resulting in increased profits. The greatest advantage of adopting Industry 4.0 is a cost-effective and high-quality mass production with 10–30% lower costs due to rapid and customizable procedures, including storage cost reductions. The potential 10–30% cost reduction in logistics and quality control is another benefit [68]. Behavior pattern clustering and virtual simulation tools, data mining and intelligent process planning algorithms, and predictive and prescriptive analytics optimize planning and scheduling data in cyber-physical production and swarm robotic systems on digital twin shop floor. Multi-robot control systems require decision and control algorithms, computational intelligence and smart manufacturing scheduling tools, and sensor-based data acquisition. Job shop scheduling, deep learning-enabled smart process planning, and data processing capabilities develop on autonomous robotized devices in dynamic industrial environments. Autonomous swarm and cognitive robots leverage real-time decision support and immersive visualization systems, industrial automation and 3D virtual simulation technologies, and image recognition and deep reinforcement learning tools in dynamic manufacturing environments.

Utilizing energy and natural resources efficiently increases labor productivity, lowers environmental damage, and increases efficiency by 15–20% [69]. As a result, the manufactured items may be produced and made accessible to customers more swiftly. By emphasizing cutting-edge industrial production practices, Industry 4.0 promotes consistent economic growth [70]. While implementing Industry 4.0, SMEs encounter dynamic hurdles. As barriers and impulses to the adoption of new technologies are connected, possible advantages of overcoming implementation challenges for SMEs will also be addressed [71]. Smart manufacturing tools, automated assembly machines, and computer vision algorithms configure digital twin-based product development. Digital twin-based manufacturing processes, smart factory data, and collaborative localization techniques configure Industry 5.0 technologies and tasks. Robotic manufacturing processes integrate cloud-based remote operations, computer vision control techniques, and modeling and simulation algorithms. Multisensor fusion technologies, cloud computing machines, and cognitive data analytics further develop autonomous operational decisions.

4. Results

4.1. Obstacles of SMEs

The contribution of SMEs to the gross value of the European economy [72] exceeds 50%. SME implementation of Industry 4.0 would likely be the most difficult process due to a lack of resources. Integration of Industry 4.0-based production systems is challenging for SMEs due to the high cost of big data analytics in real-time, which is another factor in favor of this hypothesis [73]. Insufficient financing, a less-than-competent workforce, and poor cybersecurity are the primary barriers to implementing Industry 4.0 technology. SMEs are frequently less prepared to utilize cyber-physical intelligent manufacturing [9].

Figure 4 shows the large SMEs gaps in adoption of digital technologies in many areas by diffusion rate, based on country average percentages of enterprises using the technology over the period during 2015–22.

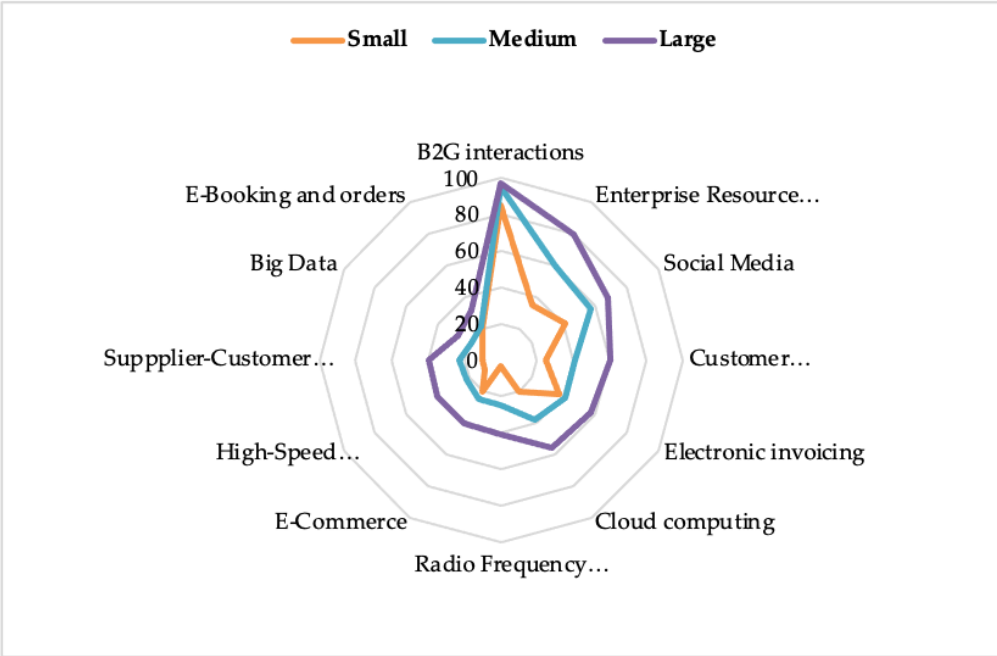


Figure 4. SME gaps in adoption are large in many areas. Source: Authors' compilation according to [73].

However, there are substantial variances amongst industries in terms of tool intensity and kind. In knowledge-intensive industries, such as information and communication services, adoption rates were far higher: the OECD median share of employees having access to devices with internet connectivity was about 90%, compared to 50% across all industries [72]. Adoption of a handful of essential technologies in each industry is crucial. In the lodging and food services industry, a high-speed internet connection, a website, and cloud computing to store data were the technologies most strongly related with better added value and bigger digital gaps. In wholesale commerce, the primary technologies that was found to drive gaps in adoption and value added were e-sales, cloud computing to host databases, and the training of ICT professionals, whereas in the retail trade, the most important technologies were e-sales and cloud computing to manage client interactions [73]. Consequently, governments should enable the access of small businesses to fundamental digital tools as an entry point to digital transformation. However, this approach must be reinforced by a sector and function-specific strategy that promotes the most relevant tools for companies.

There are six basic types of barriers to Industry 4.0 adoption [74]. Furthermore, the COVID-19 crisis has been a game-changer. Lockdowns and social alienation necessitated a radical rethinking of business models, with companies rapidly relocating operations online or developing smart working solutions in order to remain in business and overcome supply chain interruptions [65]. Initial findings from global business surveys indicated that up to 70% of SMEs increased their usage of digital technology in response to COVID-19. Given the investments made and commercial advantages of the new models, it is likely that many of these transformations will endure. Global business polls carried out lately corroborate the shift: 75% of the firms surveyed in the United Kingdom moved to remote working, and around 30% invested in new digital capabilities [63]. A total of 55% of SMEs surveyed in Brazil cited improvements in customer relationships, as well as process agility and customer acquisition, as key benefits of digitalization during the COVID-19 pandemic [70], and 72% of online small business owners surveyed in Canada believed that ecommerce is now in an incipient phase [72].

However, many organizations lack the time and guidance required to properly manage this shift—to pick the appropriate digital systems, to update digital skills, to build the appropriate safeguards and security, and to completely personalize and comprehend the potential of these new tools. For these businesses, the transformation is incomplete and fraught with danger. The increasing ability for hackers to exploit the unpreparedness of SME is a big issue. The costs associated with a data breach can be substantial and frequently exceed the ordinary SME's financial reserves. It is crucial to stress, then, that while the rapid use of digital technologies may be a silver lining to the crisis, there is an ongoing need for counsel, assistance, and direction from reputable sources to solidify changes, mitigate risks, and maximize the potential of cutting-edge tools.

The majority of 37 SMEs from various economies that participated in a study cited inadequate capital as the greatest barrier to adopting Industry 4.0. In addition, businesses highlighted a variety of obstacles that fall under this category, including a lengthy implementation process that might force production to cease, excessive costs, and questionable returns on investment. Among the obstacles are also cultural barriers associated with difficulties in departmental teamwork. Focus groups claimed that employees' limited grasp of production systems based on Industry 4.0, as well as their lack of skill and education, contributed to their fear of losing their employment. Consideration was given to the obstacles posed by an implementation method as well as to legal and technological barriers. In a study conducted in Germany, involving 68 SMEs with less than 500 employees and annual revenues of less than 50 million euros, it was determined that digitalization in SMEs was still in its infancy, and that the nature of Industry 4.0 was dependent on the size of the firm adopting it. As impediments, implementation-related organizational difficulties and significant expenditures on equipment, IT infrastructure, technical training, and IT personnel were identified. Interviewees also raised the issue of costly implementation necessitating additional costs. However, the customers' willingness to pay does not increase proportionally. The installation technique is overly difficult, the amount of automation of the machines varies, and if a single unit breaks down, the entire production might be affected. The SMEs admitted their lack of experience and the need for government or business community assistance. Respondents stated that if Industry 4.0 was not implemented, they would be driven off the market by technologically advanced competitors and would lose their customers and partners [72]. To implement Industry 4.0 in terms of sustainable product lifecycle management, SMEs require more assistance than large firms [62].

By having higher financial resources, multinational firms have greater opportunities to adopt and invest in Industry 4.0-based manufacturing systems, outperforming SMEs in terms of productivity and competitiveness. In addition to lacking financial resources, SMEs face capacity challenges that significantly limit their ability to capitalize on development opportunities. A shortage of funds has an influence on both the capacity to conduct research efforts and experience. SMEs have fewer vendors and worse networks [74]. Due to a lack of current, trustworthy, and precise information, it is difficult for SMEs to evaluate their performance and preparation for Industry 4.0. SMEs are aware of the potential long-term benefits of adopting cyber-physical manufacturing systems, but they are apprehensive of the related costs, which include the purchase of new machines, the integration of cyber-physical systems, sensors, and software, and the upgrading of existing equipment. Small- and medium-sized enterprises seek to minimize the risk of investing in the wrong technology, and they may also fear the future. Finding the most applicable technology is complex and requires managers and employees with extensive knowledge. In this aspect, SMEs require government support [75].

Due to digitalization, businesses demand leaders with the knowledge and skills necessary to oversee Industry 4.0 activities. Most small businesses struggle to locate such specialists. Detailing a project involves understanding and should include resource use and well-defined objectives. Industry 4.0 implementation involves great organization and structure. The adoption of robotic wireless sensor networks may fail if administrative and organizational procedures are not sufficiently streamlined and adaptable [76]. Data visualization and visual perception tools, blockchain and remote sensing technologies, and robotic navigation systems shape production process modeling in digital twin-based smart manufacturing. Smart product development requires modeling and simulation tools, vision sensing technology, and object recognition algorithms on the digital twin shop floor. Prescriptive and predictive analytics, edge and fog computing technologies, and image recognition and steering control algorithms enable manufacturing operations management in cyber-physical production systems.

Figure 5 demonstrates that the greatest difficulty for SMEs across all industries is not a lack of financial resources, but rather insufficient educated labor.

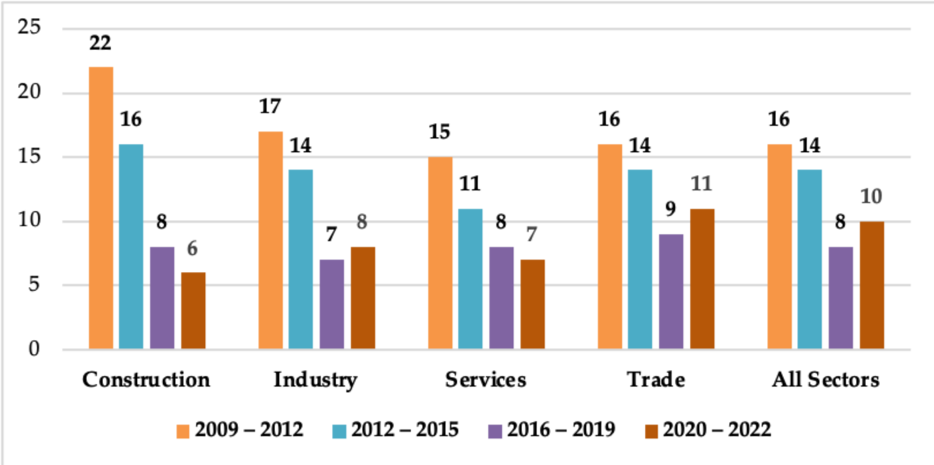


Figure 5. Most relevant issues encountered by euro area SMEs throughout industries (access to finance—weighted percentage of surveyed). Source: Adapted from Ref. [77].

As business collaboration was described briefly, the social context must be analyzed. Social capital may be divided into internal and external components. Internal social capital is a measure of collaboration and a depiction of the bonds between employees inside a particular organization. External social capital is characterized by connectivity and collaboration with other external companies and institutions. Social environment is necessary for the implementation of Industry 4.0. Successful implementation of Industry 4.0 demands strong management and a dedication to establishing social connections. Collaboration with other market participants, technology and infrastructure suppliers, technological specialists, etc., as well as the social environment and new organizational structure of work, are crucial [62].

Financial support is pointless without the willingness and effort to integrate digital twin-based product creation, immersive visualization tools, and deep learning-based computer vision and virtual simulation algorithms. The social environment is also a factor in another difficulty, as investments are related to insufficient absorption capacity. Representing the ability to build a communicative foundation and integrate information for advancement, absorption capacity entails both the ability to gather and utilize information and the enhanced application of data-driven technologies and industrial processes [78]. The adoption of robotic wireless sensor networks, artificial intelligence-driven big data analytics, and Internet of Things-based decision support systems is dependent on managerial backing towards the Industry 5.0 environment. The management staff is also responsible for maximizing the utilization of obtained grants and financial aid. A lack of financial resources may hinder the success of the technique described above. Thus, SMEs must make prudent decisions on financial investments and teamwork [62].

Cybersecurity [72] is a significant obstacle to the integration of Industry 4.0-based production systems, robotic wireless sensor networks, and Internet of Things smart devices. Since 2021, 6 trillion dollars have been spent on cyberattacks yearly [79]. Both quantitative and qualitative methods can be used to determine the loss's magnitude. Quantitative indicators are comprised of formulas that assess the impact of a cybersecurity event on the organization, including the costs associated with replacing damaged parts, testing new parts, and installing them, as well as the necessary time to perform such tasks. Other formulas incorporate production waste and profit loss in the calculation prior to the addition of monetary penalties for the causes already mentioned. The amount of a company's impact is determined by three qualitative indicators: low, medium, and high [80]. Cybersecurity is related to financial resources, and a lack of cash might have a negative effect on it, given that a breach of cybersecurity can result in costly fines and maintaining its sufficiency requires substantial investments.

The introduction of Industry 4.0 among SMEs generates several uncertainties and threats. Due to the employment of varied approaches, technologies, and languages to integrate numerous components and tools, the success of the aforementioned process requires a flexible interface. Enterprise stability ensures the reliability of systems, and collaboration across all organizational components is required when adopting big data-driven decision-making processes, artificial intelligence data-driven Internet of Things systems, and cognitive automation tools towards the Industry 5.0 environment. Neural network and deep learning algorithms, digital twin modeling and predictive maintenance tools, and environment mapping and data stream clustering algorithms assist virtual manufacturing technologies and cyber-physical production systems. Machine monitoring and intelligence technologies, data acquisition tools, and computer vision algorithms articulate cyber-physical production systems. Data fusion mechanisms, machine control systems, and distributed sensor networks are pivotal in digital twin-based virtual factories and industrial cloud robotics. Smart product innovation develops on digital twin and industrial automation technologies, data processing and context awareness algorithms, and image processing and mobile swarm tools.

A lengthy integration procedure of Internet of Things sensing networks in SMEs may result in production delays, high costs, and an uncertain rate of return. Again, the mentioned hindrances are associated with a lack of financial resources, which might result in substantial complications during the installation of cyber-physical process monitoring systems and standard organizational operations [73]. An efficient business model controls the configuration and utilization of artificial intelligence data-driven Internet of Things and product decision-making information systems, as well as the operation planning and administration of a firm. SMEs may analyze all of the challenges that adopting Industry 4.0 will provide, but they also seek to comprehend how to profit from the shift. Technological breakthroughs in business models are one of the aforementioned advances. The purpose of an innovation in a company strategy is to reduce consumer expenditures while boosting product value and customer loyalty. Utilizing autonomous production systems and spatial data visualization tools, innovations may be implemented. On the one hand, SMEs claim that it is a pricey operation. On the other hand, it may have long-term benefits. When a business strategy is more demand-driven, customers' willingness to pay may increase. Therefore, everything that originally appears to be a difficulty may ultimately become useful [72].

4.2. Financial Backing for SMEs

The expansion of SMEs is fostered by a number of organizations, as they are crucial for social progress and a vibrant economy. The primarily EU-provided financial aid for SMEs is discussed in the following sections. The difficulties of collecting financial resources are next emphasized, followed by a discussion of the government's involvement [81]. The EU provides SMEs with a range of financial support options, including grants and loans, guarantees, assistance, and financing for particular projects or new businesses. EU grants are financial instruments meant to enhance a nation's performance, aid varied industries, and advance economic development. Indirectly or directly, the EU supports state funds that subsidize several activities inside Europe. SMEs benefit from European Investment Fund-administered grants. The number of EU investments demonstrates that SMEs are among the top recipients of financial assistance. From 2014 to 2020, the EU invested one trillion euros on a range of initiatives within the EU [82]. The implementation of Industry 4.0

might be extremely useful for SMEs, but at a high cost [62]. The European Investment Bank (EIB) and the European Investment Fund (EIF) comprise the EIB Group, which is largely responsible for SME finance and digitalization. Figure 3 illustrates how the European Commission decides on the allocation of financial resources and how it communicates with the EIB Group and the management bodies of member states [64]. The EIB makes loans via intermediaries such as commercial banks. These loans are designed for SME investments in tangible and intangible assets and serve as the cornerstone for SME access to sustainable operational capital and long-term financing needs [82]. Due to their significance for the European economy, SMEs are the principal focus of financial support efforts. Funding comes from financial institutions in European member states. There are several types of financial assistance, including loans, guarantees, microfinance, and equity funding. One way to allocate cash is through organizations that establish the conditions and criteria of financing (e.g., social investors, business angels, crowdfunding partners, and venture capital funds) [64]. The EIF's major objective is to facilitate access to funding for SMEs (Figure 6).

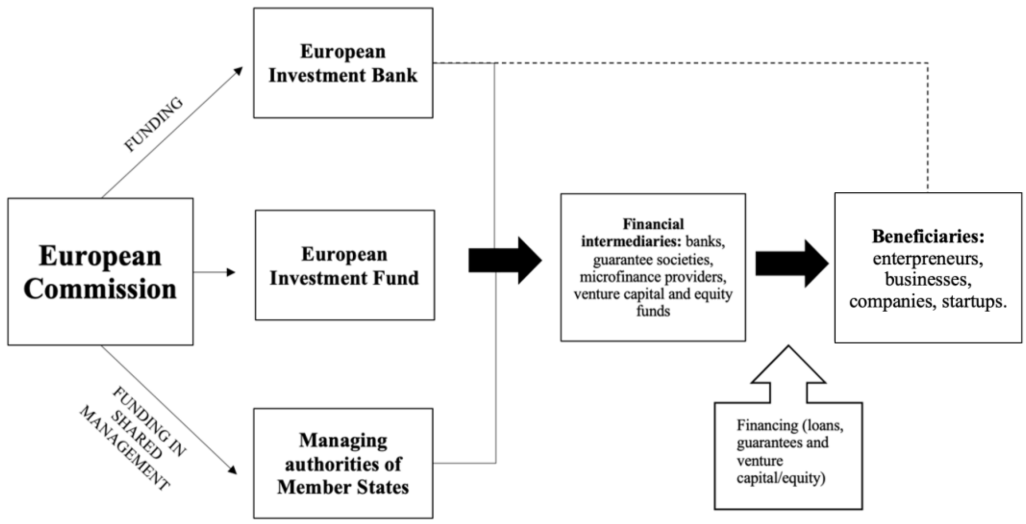


Figure 6. The scheme of financial support by EU Institutions. Source: Authors' compilation.

The following are brief descriptions of the approaches employed by the EU to promote innovation, digitization, and SME growth in Europe. Whether SME adoption of Industry 4.0 is hampered by a shortage of capital or not, it is crucial to examine the ease of access to external funding for such companies to see if certain impediments may be removed.

The Programme for the Competitiveness of Enterprises and Small and Medium-Sized Enterprises (COSME) and the European Fund for Strategic Investment collaborate to promote the digital transformation of SMEs. By subsidizing financial instruments, budgetary resources are used to facilitate access to loans and finance. The leverage effect is also utilized with regard to budget. Approximately 35 billion euros can be raised via financial intermediaries [83]. COSME is dependent on the Loan Guarantee Facility, which focuses mostly on digitalization (LGF). In 2019, the European Commission and EIF launched the COSME LGF. This COSME digitalization experiment focuses primarily on the digital transformation of SMEs, since the EU is aware that a lack of financial resources is a key impediment to digitalization. Loans backed by COSME guarantees will aid about 500,000 SMEs [84]. More than thirty billion euros has been lent thus far. COSME also includes the Equity Facility for Development (EFG), which is administered by the EIF and promotes the growth and expansion of SMEs. According to [85], 300 enterprises will benefit from the EFG's 2.54 billion euro investment.

Horizon Europe's predecessor was Horizon 2020, a research and innovation project with a 77-billion-euro budget that ran from 2014 to 2020. The suggested program placed a heavy emphasis on assisting SMEs and eradicating barriers to innovation. Horizon Europe now manages a total budget of 95.5 billion euros for the years 2021 to 2027. Principal investment areas will include digital transformations, the growth of research and technology, industrial competitiveness, innovation, and teamwork. The objective of this initiative is to reduce the administrative burden on applicants [82]. Horizon Europe, with a €10 billion budget for 2021–2027, comprises the European Innovation Council (EIC). Its grants and investments mostly target SMEs. During the EIC trial period of 2018–2020, more than 5700 new businesses and SMEs received about 5 billion euros in benefits and more than doubled their workforce. It is projected that 372 billion euros will be raised for Europe's investment plan for 2021–2027. Among the plan's primary areas of emphasis are research, innovation, and the digitization of EU industry. The financial aid focuses mostly on facilitating and enhancing the finance process for SMEs [86].

The principal objectives of the DIGITALEUROPE organization are the digitalization of all European industries and the establishment of a society that can leverage deep learning-assisted smart process planning, cyber-physical system-based real-time monitoring, and artificial intelligence-based decision-making and virtual simulation algorithms. DIGITALEUROPE's activities include legislation, the establishment of industrial policy perspectives, and the implementation of digitalization policies throughout Europe. To ensure a sustainable and competitive production, the EU pioneered the concept of "Factories of the Future" and encouraged enterprises to join public–private partnerships. In addition, enterprises with complementary competences might be amalgamated as part of government and industry initiatives [72]. Industry 4.0 wireless networks and the establishment of Factories 4.0 are the primary issues of the EU's public–private partnership for innovation and cutting-edge production research, which also involves SMEs and other organizations. By 2030, the EU intends to transform itself into a digital economy. This perspective's goals cover the digital transformation of businesses, which will enable more than 90% of SMEs to achieve a minimum level of digitization. Additionally, emphasis will be made on worker education and the development of Industry 4.0-related laws. From this initiative, it is reasonable to conclude that the EU is dedicated to aiding SMEs and digitalization [64].

4.3. Barriers to Acquiring Financial Support

The difficulty of obtaining financing has an effect on the operation of SMEs. Nonetheless, the euro area's financial access is improving. Access to external resources is only a significant issue for 8% of SMEs. Nevertheless, as shown in Figure 7, larger firms have better access to external financing than smaller ones [77].

Businesses may have difficulty receiving external financing due to their reluctance to seek for it out of fear of rejection, or because they would receive an unacceptable loan amount or one with a high interest rate. The documentation needed in submitting a request for financial help may be time-consuming and onerous, representing a potential barrier. Other factors, such as the company's age and amount of innovation, may influence the ease with which SMEs can get external financing [77]. As seen in Figure 8, small and developing enterprises have the most difficulties in acquiring external finance. As a result of more uncertainty, the possibility of receiving financing is diminished for enterprises whose major focus is on creative operations, despite the fact that mature SMEs have better possibilities. Due to the fact that many SMEs rely solely on a single source of capital, financing strategies should be diversified.

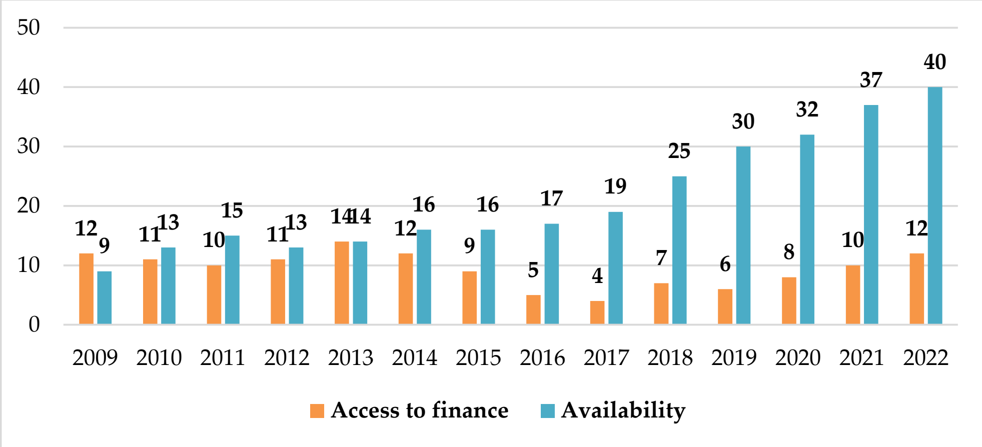
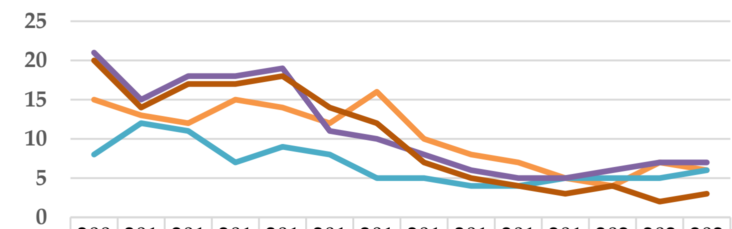


Figure 7. Most significant problems faced by euro area firms (weighted percentage of respondents). Source: Adapted from Ref. [77].



	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
SMEs	15	13	12	15	14	12	16	10	8	7	5	4	7	6
Large enterprises	8	12	11	7	9	8	5	5	4	4	5	5	5	6
SMEs – young	21	15	18	18	19	11	10	8	6	5	5	6	7	7
SMEs – innovative	20	14	17	17	18	14	12	7	5	4	3	4	2	3

Figure 8. Financially limited firms according to age and size (weighted percentage of surveyed). Source: Adapted from Ref. [77].

SMEs have limited access to financial resources, and acquiring funding is an expensive procedure. Investors will only fund SMEs if it is possible for them to purchase a piece of the firm. The majority of investors wish to work in management. However, they may leave after selling their share to a subsequent investment or to the original owner. Due to their opposition to the future sale of shares, SMEs may have a negative attitude toward new shareholders. Another challenge is that it may be difficult for SMEs to utilize instruments for risky investments [87].

Governments are in the process of enacting legislation and launching programs to financially support the digitization of enterprises. This assistance is provided by financial resources and institutional activities to promote the external partnerships of firms with universities, middlemen, other businesses, and technology suppliers, among others. Moreover, support for educational and training activities is a desired outcome. These activities are geared toward SMEs because they are the ones suffering mostly with Industry 4.0. As a result of current government efforts [62], some SMEs have invested in manufacturing technologies powered by big data and enhanced their partnerships with external partners. Direct and indirect forms of financial assistance can be divided into two distinct groups. Included in direct forms are grants from European funds, export premiums, extra fees, etc. Indirect financial support includes tax rebates, reduced interest rates, and financial assurances, among other things. There is a huge network of organizations trying to assist SMEs at the state, regional, and local levels within nations.

Finding methods for government and industry to collaborate is vital, since this affects both intrastate and international connections [15]. Inadequate finance and cost-cutting measures may have an influence on national affairs; thus, the government should aid businesses in their transition to Industry 4.0. Cybersecurity, for instance, impacts state-to-state relations as well as international security, while unemployment leads to social imbalance [85].

4.4. Persistent, Long-Term Structural Obstacles

In addition to the requirement for access to the correct guidance and motivation, there are additional structural impediments to digital adoption, including: (i) an internal skills gap that prevents managers and workers from identifying the digital solutions they need, and to adapt business models and processes; (ii) a financing gap, as SMEs face difficulties in accessing finance for intangible digital investments that cannot be easily used as collateral to secure a loan; and (iii) an infrastructure gap. Access to high-speed broadband is a prerequisite for the digital transformation of SMEs [67]. Penetration rates of high-speed broadband have been increasing in all OECD countries since 2011, but the leading countries and firms have been pulling away from the rest (Figures 9 and 10), and gaps between firms in lagging countries have widened significantly. Access to high-speed broadband is still uneven, and development for small businesses has halted.

These disparities have made it difficult for some businesses and locations to change their business models and continue operations over lengthy periods of social estrangement, hence aggravating existing disparities. The SME Digital initiative in Denmark and the Australian Small Business Advisory Service offer financial and consulting assistance, while Chile, Israel, Latvia, and Spain provide SMEs with skill training. There are infrastructure improvement strategies in Iceland and Costa Rica, as well as networking programs in Belgium and Germany. These efforts will play a significant role in addressing the digital gap, but they must be well-coordinated through multilevel governance and processes that link thematic expenditures (for example, ensuring that the provision of infrastructure is supported by training and advice to enable their use) [78].

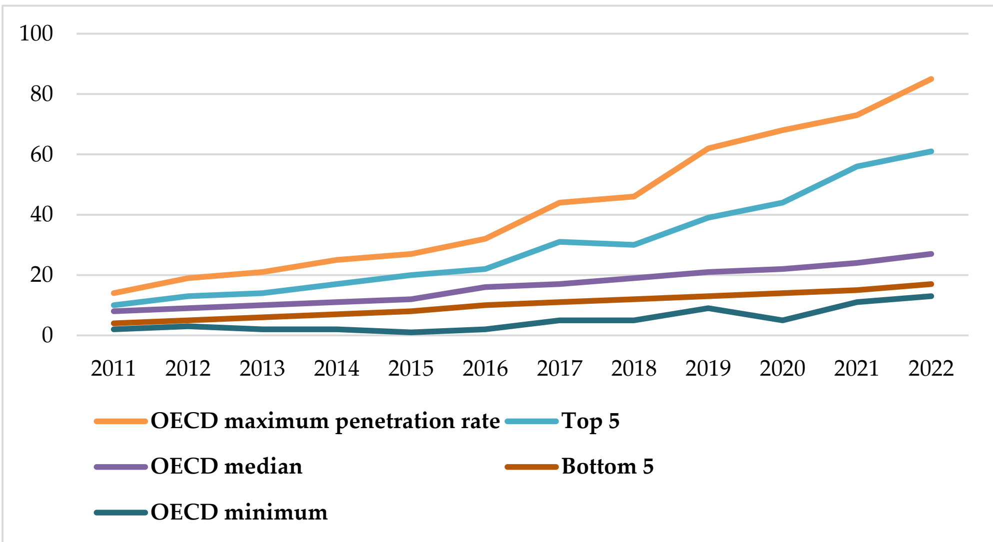


Figure 9. Differences in penetration rates across nations, 2011 to 2022. Source: Adapted from Ref. [77].

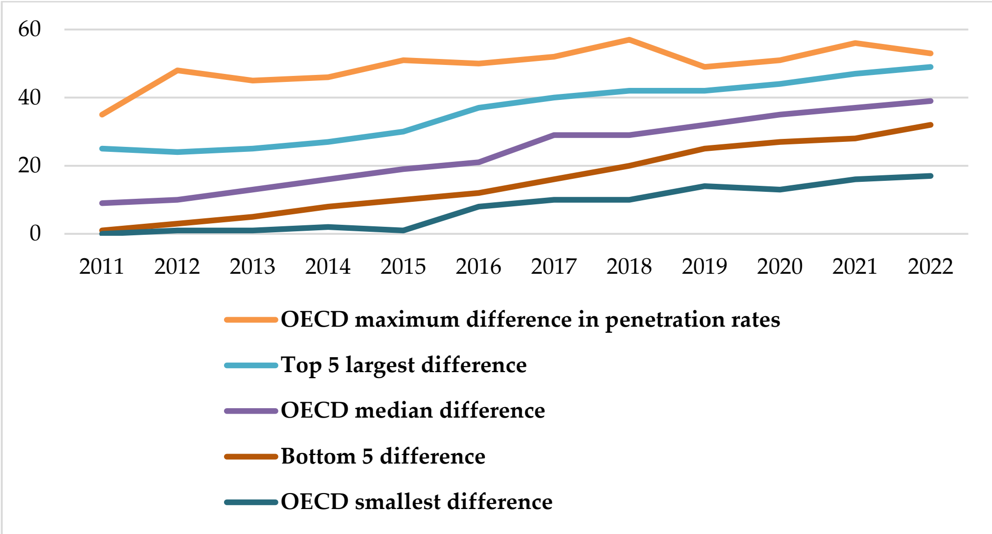


Figure 10. Differences in penetration rates across small and large firms, 2011 to 2022. Source: Adapted from Ref. [77].

4.5. Government Support for Digitalization

The government's backing and style of administration are the foundation for the digital age's good functioning and support. Available funds should be invested for the advancement of science and technology. Businesses are also encouraged in this direction, since they hold the key to the future of company and the education of future digital era employees. This section of the work includes proposals and activities that national governments should undertake on the path to digitalization.

Table 5 shows four measures taken by the government to promote the digital transformation of SMEs. This section of the text examines these four processes from several perspectives for a more comprehensive examination.

Table 5. Government boost for digitization.

4 Steps from Government to Boost the SME's Digital Transformation:
1. Scaling up SME internal capacity
2. Easing SME access to strategic resources
3. Creating the right business environment for SME transformation
4. Promoting a whole-of-government approach

Source: Authors' compilation.

Increasing the internal capacity of SMEs: (1) Providing technological support and assistance to SMEs through targeted financial support (consultancy vouchers, grants), technology extension programs (diagnostic, self-assessment tools, e-business solutions, advice and a bundle of learning materials), or a combination of the two. (2) Encouraging SME training and upskilling [27], by reducing training costs (e.g., tax incentives and subsidies) and promoting workplace training (e.g., via employer networks and associations, intermediary brokers, apprenticeships programs, etc.) or by pooling training investments. (3) Strengthening management skills in SMEs (e.g., through training, workshops, and coaching programs). (4) Building a data culture in SMEs, by increasing awareness of the benefits of data analytics.

Easing SME access to strategic resources: (1) Leveraging fintech and alternative sources of finance for SMEs, by promoting the use of new technologies (such as blockchain and AI) to lower transaction costs on finance markets; encouraging the deployment of financing and matching marketplaces, as well as the use of mobile banking [14], or alternative data for credit risk assessment. (2) Encouraging business innovation and the supply of new digital solutions, through a range of research and innovation policies (e.g., research and development, and research and development tax credits). (3) Connecting SMEs with knowledge networks, through cooperation programs (e.g., with large firms or online platforms) or SME-led public procurement (e.g., Small Business Innovation Research-type of program) or networking interfaces (e.g., digital innovation hubs, centers of excellence, clusters, and co-working spaces). (4) Providing SMEs with access to data and technology, via testbeds and experimentation labs, data centers, digital innovation hubs, university transfer offices, and university transfer offices.

Creating the appropriate business environment for small business transformation: (1) Establishing a supportive regulatory framework by: reinforcing efforts to harmonize legislations on trade secrecy and intellectual property rights protection across jurisdictions; enforcing data protection regulations; developing digital security legislations and establishing industry standards; addressing regulatory uncertainties surrounding distributed ledger technologies; and ensuring the smooth operation of knowledge markets where SMEs can access digital solutions [69]. (2) Promoting e-government and e-services for SMEs through one-stop shops and digital portals (e.g., for information provision, or assistance, certification, or simulation online, the "only once principle"); e-invoicing, e-signature, and electronic submissions (e.g., tax administration and compliance by default); adoption of new digital technologies in public services (e.g., blockchain and artificial intelligence); through open government data, etc. (3) Deploying high-quality digital infrastructure via development plans and roadmaps (e.g., high-speed broadband and connectivity in remote areas) or other platforms (e.g., computer emergency response teams) or public-sector-backed blockchain service infrastructure with interoperability with private sector platforms [88].

Promoting a whole-of-government approach: (1) Creating governance arrangements in emerging policy areas through artificial intelligence or blockchain (e.g., coordination bodies and structures). (2) Establishing consultation instances and advisory groups at national and subnational levels, with the participation of experts, entrepreneurs, industry and academics, and local governments, in order to promote ethical and more responsible digitization policies [89].

This section concludes by discussing the research and development investment of EU governments (government budget allocations for R&D (2021) € per person) (Figure 11), which is definitely tied to digitization and the preparedness of working people for this change. The subsequent graph illustrates the resolved issue and highlights the need for a stronger emphasis on R&D in nearly all EU nations.

Comparing 2011 (€184 per person) to 2021 (€244 per person), government budget allocations for R&D in the EU increased by 33%. The greatest allocations were reported in Luxembourg (689 euros per person), followed by Denmark (530 euros) and Germany (471) by a considerable margin. Romania (19 euros per person), Bulgaria (24 euros per person), Latvia (45 euros per person), and Hungary (60 euros per person) had the smallest R&D budget allocations per capita. Latvia (from €14 in 2011 to €45 in 2021), Greece (from €58 to €152), and Hungary (from €30 to €60) have had the biggest percentage growth in government budget expenditures for R&D per person during the past decade. In contrast, in Spain, these allocations declined from €155 in 2011 to €152 in 2022. R&D is important to several European and state programs that aim to boost the competitiveness of EU economies and the well-being of EU inhabitants. In the Political Guidelines for the next European Commission for the period of 2019 to 2024, R&D was identified as a driving topic.

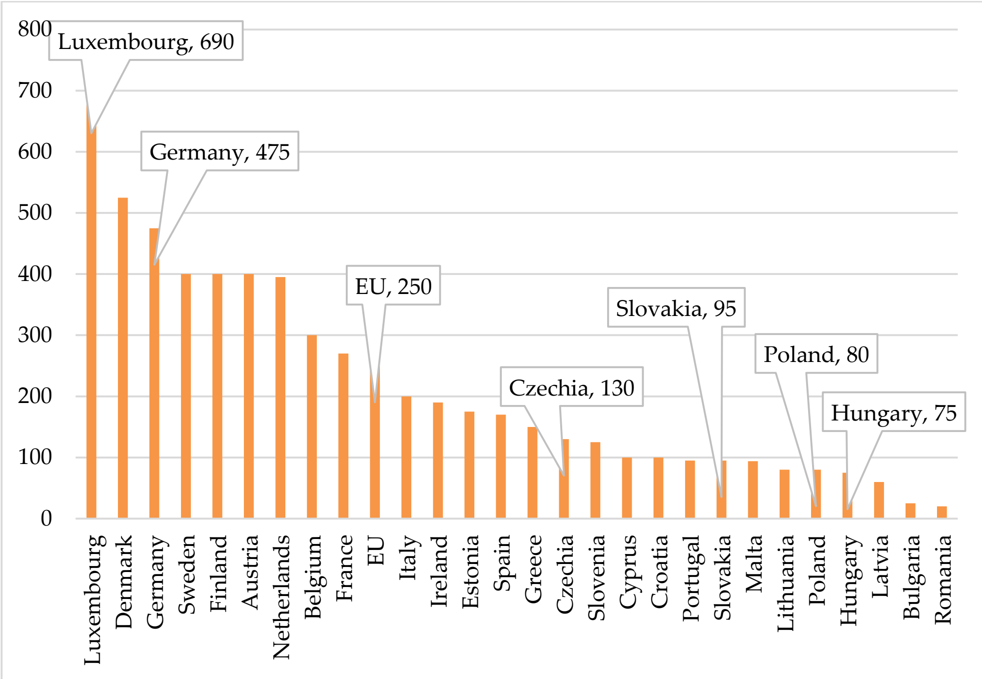


Figure 11. Government budget allocations for R&D (2021, € per person). Source: Adapted from Ref. [77].

5. Discussion

The initial part of the study focused on deciphering the nomenclature around Industry 4.0 and the underlying technologies. These new ideas were briefly reviewed in order to better comprehend the meaning of Industry 4.0, which is crucial for the implementation process. The evaluation of the advantages and disadvantages of implementing Industry 4.0 followed this section. Among the upsides, optimized environment, efficiency, quality, competitive prices, and economic growth can be mentioned [89]. One downside [90] is the need to overcome difficulties such as massive data storage, human training, a lack of finance, etc. Additionally, the preparedness of businesses was analyzed, and it was determined that the majority of enterprises of varying sizes were not equipped to install production systems based on Industry 4.0. The research's major focus was on barriers to the adoption of cyber-physical production networks, deep learning-assisted smart process planning, and industrial big data analytics [91]. The most often stated obstacles were a lack of finance and qualified employees. The competitiveness and a lack of willingness to accept new technology were also mentioned [92].

The two primary hurdles, social environment and financial resources, are intertwined. The partnership of firms, which was recommended to businesses as a strategy to combat possible vulnerabilities, such as a shortage of qualified labor, may be utilized to explain how interconnectivity works [93]. But for collaboration to be effective, financial resources for digitalization are necessary [94–97]. The benefits of collaborating with other businesses and creating new business models were then discussed. SMEs and large corporations do not have equal opportunities to embrace Industry 4.0 technologies. Moreover, they have diverse purposes and foci, the combination of which might be useful [98,99]. Large corporations can benefit from the flexible production and competitive edge of SMEs. Nevertheless, many difficulties and goals are shared by firms of all sizes, such as the need for skilled labor and the pursuit of high productivity [100–102]. Numerous SME owners cited a lack of financial resources as their principal difficulty; hence, it was essential to explore the veracity of this assertion and possible alternatives. It was determined that the EU helps SMEs because it benefits from their success. To support this claim, a list of EU programs that assist SMEs was provided. There are several alternatives for financial help, but their acquisition might be difficult by a number of factors, including age, size, and subject of study. The limitations of the study are discussed at the conclusion of the report since its accuracy required verification. In the first place, there are insufficient scholarly resources addressing the study's specific concerns. Although it appears that sufficient sources were employed to generate this research, it is still hard to draw certain findings [103–105]. As was previously stated, while considering Industry 4.0, researchers are more inclined to focus on large corporations.

There is insufficient evidence to support the dynamics of SMEs in the cyber-physical production environment in connection to the aforementioned difficulties performed and utilized in this study. In addition, not all European economies have been considered or examined. Therefore, the findings should not be used to describe the status of SMEs across Europe. Since studies usually focus on big economies such as China, the United States, or India, a portion of the information on the benefits and downsides of implementing Industry 4.0 was derived from U.S. research. As technology evolves at an extraordinary rate, a new source-related problem emerges. Due to the rapid evolution of technology and Industry 4.0, academic materials from only a few years ago may now be obsolete [106]. Since the situation of the COVID-19 pandemic was not considered when conducting this inquiry, it is difficult to predict the future of Industry 4.0. Due to the unfavorable economic climate, businesses may be compelled to embrace Internet of Things-based real-time production logistics as soon as possible in order to minimize the number of operational staff, or it may become a substantial barrier.

On the basis of the observation of successful collaboration between large organizations, it is recommended that SMEs collaborate [107]. Since there is little evidence of effective collaboration between SMEs and large businesses, this explanation for hypothetical situations based on the available data is extremely rational. It was found that EU support may help alleviate the lack of financial resources [61]. However, there are no affirmative comments from SMEs on whether the financial assistance is sufficient [45]. Again, this can only be extrapolated from the facts currently known, such as the quantity of the funding dedicated to aid and the EU's strong desire to help SMEs. Due to the scarcity of considerable amounts of data, the partnership of SMEs and major corporations, the distribution of financial resources received via grants, and the costs involved with the recruitment of talented personnel, all require more research [108]. 3D convolutional neural networks, computer vision and path planning algorithms, and intelligent data processing and smart environment modeling tools configure cyber-physical production and virtual manufacturing systems. Multiple autonomous mobile robots, deep learning-based image processing and context awareness algorithms, and ambient intelligence and visual analytics tools articulate shop-floor production management [109,110]. Spatial data acquisition and context recognition tools, machine perception and simulation modeling technologies, and connected mobile devices assist manufacturing execution and robotic operating systems. Wireless sensor networks, space situational awareness and computational intelligence tools, and decision support systems enable product lifecycle monitoring and autonomous mobile robot navigation across smart shop floors [111–114]. Virtual reality-based data analytics, cognitive decision-making algorithms, and deep convolutional neural networks increase industrial control and automation systems. Image recognition and crowd navigation algorithms, sound recognition systems, and ambient intelligence and predictive simulation tools optimize smart manufacturing machines in immersive 3D and Industry 5.0 environments [115–118]. Machine intelligence and digital twin technologies harness situational awareness and remote sensing algorithms, cloud-based cyber-physical systems, and image acquisition devices in Industry 4.0-based networked environments. Digital twin technologies leverage simulation analytics, environment perception sensors, and cognitive data fusion techniques in smart manufacturing processes [119–122].

Cyber-physical production and autonomous manufacturing systems integrate sensor fusion capabilities, robotic navigation processes, and smart process planning. Robotic cooperative behaviors require digital twin-driven product development, enterprise resource planning, and process performance monitoring [123–128]. Real-time data visualization and cognitive artificial intelligence tools, virtual equipment and robotic cooperation systems, and predictive modeling and deep learning algorithms are instrumental in visual simulation environments. Industry 5.0-driven sustainable operations necessitate monitoring and sensing technologies, cloud-based production processes, and virtual mapping and data mining tools [129–132]. Data fusion mechanisms, machine control systems, and distributed sensor networks are pivotal in digital twin-based virtual factories and industrial cloud robotics. Job shop scheduling, deep learning-enabled smart process planning, and data processing capabilities develop on autonomous robotized devices in dynamic industrial environments. Swarm computing and motion control algorithms, visual and spatial intelligence tools, and cloud computing technologies shape autonomous task allocation and production process modeling in digital twin-driven smart manufacturing [133–136]. Shop floor digital twins deploy real-time operational data, smart connected sensors, and 3D spatio-temporal simulations in virtual manufacturing systems and across collaborative multi-robot environments. Digital twin-based manufacturing processes, smart factory data, and collaborative localization techniques configure Industry 5.0 technologies and tasks. Networked robots, machine data fusion, and predictive analytics algorithms articulate digital twin-based intelligent manufacturing in the Industrial Metaverse [137–140] (Table 6).

Table 6. Main research findings.

• Interoperable production and dynamic operating systems, data virtualization technology, and digital twin modeling and virtual simulation tools configure smart shop floors and manufacturing environments in the corporate context of SMEs.
• Virtual data modeling and process mining tools, big data sensing systems, and image recognition and robotic behavior algorithms articulate cyber-physical production networks and digital twin-based manufacturing systems.
• Data modeling technologies, visual perception and spatial mapping algorithms, and digital twin and decision support tools shape Industry 4.0-based manufacturing systems and virtual robotic environments.
• Machine intelligence and autonomous robotic technologies optimize smart manufacturing plants and virtual enterprises by use of context modeling and data mining tools, collision avoidance and coordinated motion planning algorithms, and digital twin processes.
• Digital twin-based smart production develops on virtual process modeling and visual navigation tools, deep learning-enabled process planning technologies, and perception and cognition algorithms.
• Smart manufacturing systems integrate deep learning and virtual simulation algorithms, real-time machine and shop floor data, and intelligent sensing devices across dynamic unstructured environments.

Source: Authors' compilation.

6. Conclusions

Regarding artificial intelligence-driven decision-making and virtual simulation algorithms, cyber-physical production networks, and Industry 4.0-based manufacturing systems, the two largest impediments to the adoption of Industry 4.0-based manufacturing systems are a lack of financial resources and a skilled labor force, according to the comments of various SME leaders in Europe.

Because all the barriers highlighted in this study are interconnected and certain extra obstacles that SMEs may face are closely related to them, it does not appear possible to choose one as the most significant. Cybersecurity faces these challenges adequately and these challenges may be precisely addressed by combining a trained workforce with sufficient financial resources. To embrace Industry 4.0, organizations require dedicated owners and adaptable managerial support, as well as the willingness to seek external financing if necessary. The SME sector is a top priority for the EU, and there are several alternatives for financial assistance. After receiving this advice, the management staff will be in a better position to design a clear strategy, select the subsequent digitalization approaches, and incur more costs. The management staff, which is comprised of educated and competent individuals, may also provide people assistance, which includes monitoring the growth of their training and abilities. The management staff may also assist internal and external cooperation inside organizations that can handle a range of problems encountered by SMEs including artificial intelligence-based decision-making and virtual simulation algorithms, real-time sensor networks, and cyber-physical system-based manufacturing [141–144].

Even if SMEs had the financial means, the implementation of Industry 4.0 would fail without a solid plan and comprehension. The necessity for a highly educated and skilled workforce or the cost of their training may result in an increase in labor expenses, making the social environment crucial but also demanding substantial financial resources. The most important factors for a company's adoption of Industry 4.0 are a proper grasp of the concept and its subsequent incorporation into the organization via an appropriate management structure and sufficient support from skilled executives. Because Internet of Things-based decision support systems require significant financial resources, the initial assumption that only large businesses can adopt Industry 4.0-based manufacturing systems is only partially accurate, as SMEs can request additional financial resources.

Additionally, the deployment of sustainable manufacturing Internet of Things and robotic wireless sensor networks need further development. In order to evaluate the reality of the assertion that, in the context of Industry 4.0, the gap between large enterprises and SMEs will severely hurt the latter, it is legitimate to conclude that some inequality exists. Consequently, SMEs must exert greater effort to compensate. Industry 4.0 implementation is essential if a company aspires to surpass its market competitors. Despite the fact that SMEs and large organizations may not have equal opportunities, SMEs are not always driven off the market by large corporations. Collaboration between businesses is crucial, and SMEs may develop links with large firms by using their adaptability and competitive edge. The potential benefits are sufficient to motivate firms to embrace cyber-physical production networks and artificial intelligence-based decision-making and virtual simulation algorithms notwithstanding the presence of certain barriers [145–148]. Ahead-of-the-curve businesses that have already successfully integrated deep learning-assisted smart process planning, big data-driven decision-making processes, and Internet of Things smart devices may demonstrate the real benefits and advancements that can be realized by adopting Internet of Things-based real-time production logistics [149–151].

Companies are uncertain about the outcome of this endeavor since the difficulties associated with Industry 4.0 adaptation are usually too complex for an outsider to know in full. As a result, more research must be conducted in several fields. As is the case with the use of big data, for instance, what is initially perceived as a gain may turn out to be a drawback. Real-time access to information is a big advantage. The requirement to deal with voluminous data that necessitates storage, cybersecurity, etc., is also taxing on staff. Another example that should be seen favorably is automation. The acceptance of this tendency might, however, be accompanied with automation bias or the paradox of automation. Based on a few incidents, every organization aiming to implement all the technologies presently in development should take caution. Despite the effort to conduct a detailed analysis, it is possible to claim that the study has a number of flaws, such as secondary and insufficient data.

In addition, conducting the analysis with more European states would be desirable. On the other hand, the research emphasizes the most recent industry trend and draws attention to the associated economic concerns, which may be viewed as an added advantage. Industry 4.0 is evolving on a global scale; thus, it will take some time to determine the exact effect and potential obstacles. In addition, the COVID-19 pandemic may push firms to refocus their attention on more pressing issues, which will hinder their willingness to adopt new technology. Political, social, and economic institutions must adapt to a vast array of new technological advances in all industrial sectors, not just manufacturing. If stakeholders and managers of large-scale industrial companies desire sustainable economic growth for the future of mankind, they are obligated to collaborate and work together to get a deeper understanding of the opportunities and challenges of Industry 4.0.

7. Specific Contributions to the Literature

Our article puts forwards machine intelligence and autonomous robotic technologies in the corporate context of SMEs in terms of deep learning and virtual simulation algorithms, cyber-physical production networks, and Industry 4.0-based manufacturing systems, a hot emerging topic that has not been analyzed so far. Our analyses prove that machine vision and cloud computing technologies, spatial data processing and cognitive artificial intelligence tools, and digital twin modeling assist production planning and scheduling in smart manufacturing environments. Big data analytics, artificial neural networks, and virtual twinning techniques enable autonomous manufacturing processes throughout industrial cyber-physical systems. Multisensor fusion technologies, cloud computing machines, and cognitive data analytics further autonomous operational decisions. Data visualization and visual perception tools, blockchain and remote sensing technologies, and robotic navigation systems shape production process modeling in digital twin-based smart manufacturing. Visual tracking and motion planning algorithms, digital twin technologies, and localization and navigation tools optimize autonomous manufacturing processes on the product assembly shop floor. Smart manufacturing enterprises necessitate signal and image processing tools, product digital twins, and motion sensing capabilities.

Virtual machine and ambient intelligence tools, obstacle detection and immersive visualization technologies, and computational prediction and image enhancement algorithms are instrumental in synthetic simulation environments. Cognitive manufacturing and cooperative multi-robot systems deploy sensor–actuator networks, spatial data analytics, and location identification and natural language processing tools. Collaborative autonomous systems leverage image acquisition and processing tools, mobile robotic devices, and cloud computing analytics in smart manufacturing environments. Production process modeling develops on predictive maintenance tools, remote sensing algorithms, and data fusion technologies. Digital twin-driven smart manufacturing integrates immersive virtual reality simulations, imaging and sensing tools, and data analytics technologies. Smart product development requires modeling and simulation tools, vision sensing technology, and object recognition algorithms on the digital twin shop floor. Autonomous cyber-physical and robotic operating systems harness industrial wireless sensor networks, interconnected virtual devices, and product lifecycle data. Big manufacturing data, cyber-physical production systems, and smart interconnected robots are pivotal in Industrial Internet of Things.

Digital twin systems harness object perception and virtual shop floor operations, captured image data, and visual modeling and multi-machine cooperation tools. Autonomous robotic and digital twin-enabled industrial systems deploy data processing and context awareness algorithms, edge computing technologies, and modeling and simulation tools across smart manufacturing plants. Autonomous swarm and cognitive robots leverage real-time decision support and immersive visualization systems, industrial automation and 3D virtual simulation technologies, and image recognition and deep reinforcement learning tools in dynamic manufacturing environments. Smart product innovation develops on digital twin and industrial automation technologies, data processing and context awareness algorithms, and image processing and mobile swarm tools. Robotic manufacturing processes integrate cloud-based remote operations, computer vision control techniques, and modeling and simulation algorithms. Autonomous and collaborative robots require spatial data visualization and assembly process planning tools, multisensor fusion and cloud-based digital twin technologies, and motion control and context awareness algorithms throughout augmented operating environments. Virtual machines necessitate blockchain-based data acquisition, intelligent manufacturing equipment, and robotic communication systems.

8. Limitations and Further Directions of Research

The scope of this research does not advance object perception and path planning algorithms, predictive simulation and image processing tools, and mobile sensors and actuators in digital twin-driven manufacturing systems. Big data analytical and acoustic environment recognition tools, computer vision and swarm intelligence algorithms, and artificial neural networks configure multi-agent robotic systems in digital twin environments. Condition monitoring data, plant equipment diagnosis, and digital twin capabilities are pivotal in autonomous production and virtual manufacturing systems. Additional research should address how Internet of Things-enabled control systems, data mapping and processing tools, and prognostic and diagnostic algorithms articulate manufacturing task management in smart networked environments. Sensory data acquisition and deep reinforcement learning tools, autonomous robotic and digital twin technologies, and computer vision and predictive maintenance algorithms shape machining process performance. Virtual twin data, smart interconnected and cognitive robotic devices, and machine learning and context awareness algorithms are instrumental in Internet of Things-enabled automation and process manufacturing systems.

Future research should investigate how sensing and computing technologies, autonomous visual object detection tools, and mobile robotic systems enable reconfigurable manufacturing processes. Neural network and deep learning algorithms, digital twin modeling and predictive maintenance tools, and environment mapping and data stream clustering algorithms assist virtual manufacturing technologies and cyber-physical production systems. Smart interconnected devices, swarm robotic and machine learning algorithms, and process simulation and scheduling tools articulate smart manufacturing systems and digital twin-based virtual factories. Attention should be directed to how digital twin and cloud computing technologies, navigation management tools, and convolutional neural networks further autonomous swarm robots in smart manufacturing environments. Behavior pattern clustering and virtual simulation tools, data mining and intelligent process planning algorithms, and predictive and prescriptive analytics optimize planning and scheduling data in cyber-physical production and swarm robotic systems on digital twin shop floor. Digital twin simulations, robotic operating systems and agent behaviors, and environment perception sensors configure Internet of Things-based cloud manufacturing.

9. Practical Implications

Autonomous manufacturing control, industrial wireless sensor networks, and predictive maintenance scheduling tools assist smart manufacturing systems in synthetic simulation environments. Plant maintenance scheduling and context recognition tools, machine learning techniques, and fault diagnosis systems shape cloud networked and collaborative robots. Smart manufacturing systems deploy digital twin modeling and intelligent data processing tools, robotic coordination mechanisms, and cognitive decision-making and augmented reality algorithms. Mobile autonomous robots integrate real-time monitoring and smart manufacturing technologies, cloud computing machines, and image recognition processes. Digital twin technology, cloud manufacturing processes, and virtual reality modeling tools are pivotal in industrial product lifecycle management. Smart manufacturing tools, automated assembly machines, and computer vision algorithms configure digital twin-based product development.

Prescriptive and predictive analytics, edge and fog computing technologies, and image recognition and steering control algorithms enable manufacturing operations management in cyber-physical production systems. Decentralized data analytics, Internet of Things-based decision support systems, and distributed sensor networks optimize product lifecycle management in smart factories and across collaborative industrial environments. Smart production systems leverage granular manufacturing data, computation-enabled robotic devices, and simulation and scheduling tools across digital twin shop floors. Multi-robot control systems require decision and control algorithms, computational intelligence and smart manufacturing scheduling tools, sensor-based data acquisition. Machine monitoring and intelligence technologies, data acquisition tools, and computer vision algorithms articulate cyber-physical production systems.

Digital twin-based product development necessitates automated prognostics and diagnostics tools, computer vision techniques, and simulation modeling processes in smart factories. Sensor data fusion, computer vision algorithms, and process simulation and production scheduling tools further autonomous robotic systems and smart manufacturing technologies. Cloud networked and autonomous mobile robots harness digital twin-based monitoring and intuitive decision-making tools, sensing and actuation capabilities, and vision and navigation systems. Digital twin-driven smart manufacturing develops on sensor-based data analysis, object recognition processes, and mobile context awareness systems. Deep learning-based computer vision algorithms, event modeling and forecasting tools, and big data-driven decision-making processes are instrumental in product lifecycle management systems. Digital twin simulation and real-time remote monitoring tools, wireless sensor technologies, and cognitive data mining algorithms assist smart industrial systems.

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References

1. Hatzigeorgiou, A.; Lodefalk, M. A literature review of the nexus between migration and internationalization. *J. Int. Trade Econ. Dev.* **2021**, *30*, 319–340. [CrossRef]
2. Nikulin, D.; Wolszczak-Derlacz, J.; Parteka, A. GVC and wage dispersion. Firm-level evidence from employee-employer database. *Equilib. Q. J. Econ. Econ. Policy* **2021**, *16*, 357–375. [CrossRef]
3. Petkovski, I.; Fedajev, A.; Bazen, J. Modelling Complex Relationships between Sustainable Competitiveness and Digitalization. *J. Compet.* **2022**, *14*, 79–96. [CrossRef]
4. Rojko, A. Industry 4.0 Concept: Background and Overview. *Int. J. Interact. Mob. Technol.* **2017**, *11*, 77–90. [CrossRef]
5. Teixeira, J.E.; Tavares-Lehmann, A.T. Industry 4.0 in the European Union: Policies and national strategies. *Technol. Forecast. Soc. Changes* **2022**, *180*, 121664. [CrossRef]
6. Jankowska, B.; Minska-Struzik, E.; Bartosik-Purgat, M.; Gotz, M.; Olejnik, I. Industry 4.0 technologies adoption: Barriers and their impact on Polish companies´ innovation performance. *Eur. Plan. Stud.* **2022**, 1–21. [CrossRef]
7. Yajashree, S.; Reza, M.N.H.; Malarvizhi, C.A.N.; Maheswari, H.; Hosseini, Z.; Kasim, A. The impact of technological innovation on Industry 4.0 implementation and sustainability: An empirical study on Malaysian small and medium sized enterprises. *Sustainability* **2021**, *13*, 10115. [CrossRef]
8. Kumar, A.; Nayyar, A. Industry: A Sustainable, Intelligent, Innovative, Internet-of-Things Industry. *A Roadmap Ind. 4.0: Smart Prod. Sharp Bus. Sustain. Dev.* **2020**, *12*, 1–21.
9. Horvath, D.; Szabo, R. Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities? *Technol. Forecast. Soc. Change* **2019**, *14*, 119–132. [CrossRef]
10. Gray, M.; Kovacova, M. Internet of Things Sensors and Digital Urban Governance in Data-driven Smart Sustainable Cities. *Geopolit. Hist. Int. Relat.* **2021**, *13*, 107–120. [CrossRef]
11. Abraham, A.; Au, E.; Binotto, A.; Garcia-Hernandez, L.; Marik, V.; Gomez Marmol, F.; Snasel, V.; Strasser, T.I.; Wahlster, W. Industry 4.0: Quo Vadis? *Eng. Appl. Artif. Intell.* **2020**, *87*, 85–87. [CrossRef]

12. Vaidya, S.; Prashant, A.; Santosh, B. Industry 4.0—A Glimpse. *Procedia Manuf.* **2018**, *20*, 233–238. [CrossRef]
13. Ye, C.S.; Ye, Q.; Shi, X.P.; Sun, Y.P. Technology gap, global value chain and carbon intensity: Evidence from global manufacturing industries. *Energy Policy* **2020**, *137*, 111094. [CrossRef]
14. Durana, P.; Perkins, N.; Valaskova, K. Artificial Intelligence Data-driven Internet of Things Systems, Real-Time Advanced Analytics, and Cyber-Physical Production Networks in Sustainable Smart Manufacturing. *Econ. Manag. Financ. Mark.* **2021**, *16*, 20–30. [CrossRef]
15. Schwab, K. *The Fourth Industrial Revolution*; World Economic Forum: Geneva, Switzerland, 2016.
16. Zavadska, Z.; Zavadsky, J. *Industry 4.0 and Intelligent Technologies in the Development of the Corporate Operation Management*; Belianum: Banska Bystrica, Slovakia, 2020; pp. 130–155.
17. Zabojnik, S. *Selected Problems of International Trade and International Business*; Econom: Bratislava, Slovakia, 2015; pp. 28–61.
18. Malkowska, A.; Urbaniec, M.; Kosała, M. The impact of digital transformation on European countries: Insights from a comparative analysis. *Equilib. Q. J. Econ. Econ. Policy* **2021**, *16*, 325–355. [CrossRef]
19. Clayton, E.; Kral, P. Autonomous Driving Algorithms and Behaviors, Sensing and Computing Technologies, and Connected Vehicle Data in Smart Transportation Networks. *Contemp. Read. Law Soc. Justice* **2021**, *13*, 9–22. [CrossRef]
20. Yang, F.; Gu, S. Industry 4.0, a revolution that requires technology and national strategies. *Complex Intell. Syst.* **2021**, *7*, 1311–1325. [CrossRef]
21. Lăzăroiu, G.; Androniceanu, A.; Grecu, I.; Grecu, G.; Neguriță, O. Artificial Intelligence-based Decision-Making Algorithms, Internet of Things Sensing Networks, and Sustainable Cyber-Physical Management Systems in Big Data-driven Cognitive Manufacturing. *Oeconomia Copernic.* **2022**, *13*, 1045–1078. [CrossRef]
22. Hermann, M.; Pentek, T.; Otto, B. Design Principles for Industry 4.0 Scenarios: A Literature Review. Technische Universitat Dortmund. 2016. Available online: http://www.snom.mb.tu-dortmund.de/cms/de/forschung/Arbeitsberichte/Design-Principles-for-Industrie-4_0-Scenarios.pdf (accessed on 2 May 2022).
23. Klingenberg, C.O.; Borges, M.A.V.; Antunes, J., Jr. Industry 4.0 as a data-driven paradigm: A systematic literature review on technologies. *J. Manuf. Technol. Manag.* **2019**, *32*, 570–592. [CrossRef]
24. Kovacova, M.; Lewis, E. Smart Factory Performance, Cognitive Automation, and Industrial Big Data Analytics in Sustainable Manufacturing Internet of Things. *J. Self Gov. Manag. Econ.* **2021**, *9*, 9–21. [CrossRef]
25. Marik, V. *Prumysl 4.0—Vyzva pro Ceskou Republiku*; Management Press: Prague, Czech Republic, 2016; pp. 13–18.
26. Lăzăroiu, G.; Andronie, M.; Iatagan, M.; Geamănu, M.; Ștefănescu, R.; Dijmărescu, I. Deep Learning-Assisted Smart Process Planning, Robotic Wireless Sensor Networks, and Geospatial Big Data Management Algorithms in the Internet of Manufacturing Things. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 277. [CrossRef]
27. Zhong, R.; Xu, X.; Klotz, E.; Newman, S.T. Intelligent Manufacturing in the Context of Industry 4.0: A Review. *Engineering* **2021**, *3*, 616–630. [CrossRef]
28. Svabova, L.; Tesarova, E.N.; Durica, M.; Strakova, L. Evaluation of the impacts of the COVID-19 pandemic on the development of the unemployment rate in Slovakia: Counterfactual before-after comparison. *Equilib. Q. J. Econ. Econ. Policy* **2021**, *16*, 261–284. [CrossRef]
29. Skare, M.; Gil-Alana, L.A.; Claudio-Quiroga, G.; Prziklas Druzeta, R. Income inequality in China 1952–2017: Persistence and main determinants. *Oeconomia Copernic.* **2021**, *12*, 863–888. [CrossRef]
30. Bonab, A.-F. The Development of Competitive Advantages of Brand in the Automotive Industry (Case Study: Pars Khodro Co). *J. Internet Bank. Commer.* **2017**, *22*, 28.
31. Lăzăroiu, G.; Harrison, A. Internet of Things Sensing Infrastructures and Data-driven Planning Technologies in Smart Sustainable City Governance and Management. *Geopolit. Hist. Int. Relat.* **2021**, *13*, 23–36. [CrossRef]
32. Mondejar, M.A.; Avtar, R.; Diaz, H.L.; Dubey, R.K.; Esteban, J.; Gomez-Morales, A.; Hallam, B.; Mbungu, N.T.; Okolo, C.C.; Prasad, K.A.; et al. Digitalization to achieve sustainable development goals: Steps towards a Smart Green Planet. *Sci. Total Environ.* **2021**, *794*, 148539. [CrossRef]
33. Sjodin, D.R.; Parida, V.; Leksell, M.; Petrovic, A. Smart Factory Implementation and Process Innovation. *Res. Technol. Manag.* **2018**, *61*, 22–31. [CrossRef]
34. Stark, J. *Product Lifecycle Management (Volume 2): The Devil is in the Details*, 3rd ed.; Springer: Cham, Switzerland, 2016; pp. 10–20.
35. Tao, F.; Qi, Q.; Wan, L.; Nee, A.Y.C. Digital Twins and Cyber–Physical Systems toward Smart Manufacturing and Industry 4.0: Correlation and Comparison. *Engineering* **2019**, *5*, 653–661. [CrossRef]
36. Pavlinek, P.; Zenka, J. Value creation and value capture in the automotive industry: Empirical evidence from Czechia. *Environ. Plan.* **2016**, *48*, 937–959. [CrossRef]
37. Verhof, P.C.; Broekhuizen, T.; Bart, Y.; Bhattacharya, A.; Dong, J.Q.; Fabian, N.; Haenlein, M. Digital transformation: A multidisciplinary reflection and research agenda. *J. Bus. Res.* **2021**, *122*, 889–901. [CrossRef]
38. Mergel, I.; Edelmann, N.; Haug, N. Defining digital transformation: Results from expert interviews. *Gov. Inf. Q.* **2019**, *36*, 101358. [CrossRef]
39. Andronie, M.; Lăzăroiu, G.; Karabolevski, O.L.; Ștefănescu, R.; Hurloiu, I.; Dijmărescu, A.; Dijmărescu, I. Remote Big Data Management Tools, Sensing and Computing Technologies, and Visual Perception and Environment Mapping Algorithms in the Internet of Robotic Things. *Electronics* **2023**, *12*, 22. [CrossRef]

40. Schot, J.; Steinmueller, W.E. Three frames for innovation policy: R&D, systems of innovation and transformative change. *Res. Policy* **2018**, *47*, 1554–1567. [CrossRef]
41. Brioschi, M.; Bonardi, M.; Fabrizio, N.; Fuggetta, A.; Vrga, E.S.; Zuccala, M. Enabling and Promoting Sustainability through Digital API Ecosystems: An example of successful implementation in the smart city domain. *Technol. Innov. Manag. Rev.* **2021**, *11*, 4–10. [CrossRef]
42. Horn, T.; Ola, H. Overview of Current Additive Manufacturing Technologies and Selected Applications. *Sci. Prog.* **2012**, *95*, 255–282. [CrossRef] [PubMed]
43. Vuong, T.K.; Mansori, S. An Analysis of the Effects of the Fourth Industrial Revolution on Vietnamese Enterprises. *Manag. Dyn. Knowl. Econ.* **2021**, *9*, 447–459. [CrossRef]
44. Volker, P. Augmented Reality in the Smart Factory: Supporting Workers in an Industry 4.0. Environment. In Proceedings of the IEEE Emerging Technology and Factory Automation (ETFA), Barcelona, Spain, 16–19 September 2014; Volume 3, pp. 1–4. [CrossRef]
45. Krulicky, T.; Horak, J. Business performance and financial health assessment through artificial intelligence. *Ekon. Manaz. Spektrum* **2021**, *15*, 38–51. [CrossRef]
46. Goel, R.; Gupta, P. Robotics and industry 4.0. In *A Roadmap to Industry 4.0: Smart Production, Sharp Business and Sustainable Development*; Nayyar, A., Kumar, A., Eds.; Springer: Berlin/Heidelberg, Germany, 2020; pp. 157–169.
47. Pisar, P.; Bilkova, D. Controlling as a tool for SME management with an emphasis on innovations in the context of Industry 4.0. *Equilib. Q. J. Econ. Econ. Policy* **2019**, *14*, 763–785. [CrossRef]
48. Kotlebova, J.; Arendas, P.; Chovancova, B. Government expenditures in the support of technological innovations and impact on stock market and real economy: The empirical evidence from the US and Germany. *Equilib. Q. J. Econ. Econ. Policy* **2020**, *15*, 717–734. [CrossRef]
49. Kubickova, L.; Kormanakova, M.; Vesela, L.; Jelinkova, Z. The Implementation of Industry 4.0 Elements as a Tool Stimulating the Competitiveness of Engineering Enterprises. *J. Compet.* **2021**, *13*, 76–94. [CrossRef]
50. Lamon, E.; Mattia, L.; Wansoo, K.; Arash, A. Towards an Intelligent Collaborative Robotic System for Mixed Case Palletizing. In Proceedings of the International Conference on Robotics and Automation (ICRA), Paris, France, 31 May–31 August 2020; Volume 1, pp. 9128–9134. [CrossRef]
51. Johnson, E.; Nica, E. Connected Vehicle Technologies, Autonomous Driving Perception Algorithms, and Smart Sustainable Urban Mobility Behaviors in Networked Transport Systems. *Contemp. Read. Law Soc. Justice* **2021**, *13*, 37–50. [CrossRef]
52. Kliestik, T.; Zvarikova, K.; Lăzăroiu, G. Data-driven Machine Learning and Neural Network Algorithms in the Retailing Environment: Consumer Engagement, Experience, and Purchase Behaviors. *Econ. Manag. Financ. Mark.* **2022**, *17*, 57–69. [CrossRef]
53. Popescu, G.H.; Valaskova, K.; Horak, J. Augmented Reality Shopping Experiences, Retail Business Analytics, and Machine Vision Algorithms in the Virtual Economy of the Metaverse. *J. Self Gov. Manag. Econ.* **2022**, *10*, 67–81. [CrossRef]
54. Woodward, B.; Kliestik, T. Intelligent Transportation Applications, Autonomous Vehicle Perception Sensor Data, and Decision-Making Self-Driving Car Control Algorithms in Smart Sustainable Urban Mobility Systems. *Contemp. Read. Law Soc. Justice* **2021**, *13*, 51–64. [CrossRef]
55. Nica, E.; Kliestik, T.; Valaskova, K.; Sabie, O.-M. The Economics of the Metaverse: Immersive Virtual Technologies, Consumer Digital Engagement, and Augmented Reality Shopping Experience. *Smart Gov.* **2022**, *1*, 21–34. [CrossRef]
56. Belhadi, A.; Kamble, S.; Jabbour, C.J.C.; Gunasekaran, A.; Ndubisi, N.O.; Venkatesh, M. Manufacturing and service supply chain resilience to the COVID-19 outbreak: Lessons learned from the automobile and airline industries. *Technol. Forecast. Soc. Chang.* **2021**, *163*, 120–447. [CrossRef]
57. Vinerean, S.; Budac, C.; Baltador, L.A.; Dabija, D.-C. Assessing the Effects of the COVID-19 Pandemic on M-Commerce Adoption: An Adapted UTAUT2 Approach. *Electronics* **2022**, *11*, 1269. [CrossRef]
58. Cooper, H.; Poliak, M.; Konecny, V. Computationally Networked Urbanism and Data-driven Planning Technologies in Smart and Environmentally Sustainable Cities. *Geopolit. Hist. Int. Relat.* **2021**, *13*, 20–30. [CrossRef]
59. Hamilton, S. Deep Learning Computer Vision Algorithms, Customer Engagement Tools, and Virtual Marketplace Dynamics Data in the Metaverse Economy. *J. Self Gov. Manag. Econ.* **2022**, *10*, 37–51. [CrossRef]
60. Konecny, V.; Barnett, C.; Poliak, M. Sensing and Computing Technologies, Intelligent Vehicular Networks, and Big Data-driven Algorithmic Decision-Making in Smart Sustainable Urbanism. *Contemp. Read. Law Soc. Justice* **2021**, *13*, 30–39. [CrossRef]
61. Lyons, N. Deep Learning-based Computer Vision Algorithms, Immersive Analytics and Simulation Software, and Virtual Reality Modeling Tools in Digital Twin-driven Smart Manufacturing. *Econ. Manag. Financ. Mark.* **2022**, *17*, 67–81. [CrossRef]
62. Agostini, L.; Nosella, A. The adoption of Industry 4.0 technologies in SMEs: Results of an international study. *Manag. Decis.* **2019**, *58*, 625–643. [CrossRef]
63. Galbraith, A.; Podhorska, I. Artificial Intelligence Data-driven Internet of Things Systems, Robotic Wireless Sensor Networks, and Sustainable Organizational Performance in Cyber-Physical Smart Manufacturing. *Econ. Manag. Financ. Mark.* **2021**, *16*, 56–69. [CrossRef]
64. European Commision, European Competitiveness Report 2014–2021. Available online: http://ec.europa.eu/enterprise/policies/industrial-competitiveness/competitiveness-analysis/european-competitiveness-report/index_en.htm (accessed on 29 April 2022).

65. Nica, E. Urban Big Data Analytics and Sustainable Governance Networks in Integrated Smart City Planning and Management. *Geopolit. Hist. Int. Relat.* **2021**, *13*, 93–106. [CrossRef]
66. Bednarikova, M. *Uvod Do Metodologie Vied*, 1st ed.; FFTU: Trnava, Slovakia, 2013; pp. 18–72.
67. Renjen, P. Industry 4.0: Are you ready? *Deloitte Rev.* **2018**, *22*, 9–11.
68. Poliak, M.; Poliakova, A.; Svabova, L.; Zhuravleva, A.N.; Nica, E. Competitiveness of Price in International Road Freight Transport. *J. Compet.* **2021**, *13*, 83–98. [CrossRef]
69. Corallo, A.; Lazoi, M.; Lezzi, M. Cybersecurity in the context of industry 4.0: A structured classification of critical assets and business impacts. *Comput. Ind.* **2020**, *11*, 14–18. [CrossRef]
70. Wallace, S.; Lăzăroiu, G. Predictive Control Algorithms, Real-World Connected Vehicle Data, and Smart Mobility Technologies in Intelligent Transportation Planning and Engineering. *Contemp. Read. Law Soc. Justice* **2021**, *13*, 79–92. [CrossRef]
71. Adamik, A.; Nowicki, M. Barriers of Creating Competitive Advantage in the Age of Industry 4.0: Conclusions from International Experience. In *Contemporary Challenges in Cooperation and Coopetition in the Age of Industry 4.0*; Springer: Cham, Switzerland, 2020; Volume 24, pp. 3–42.
72. Muller, J.; Buliga, M.; Voigt, K. Fortune favours the prepared: How SMEs approach business model innovations in Industry 4.0. *Technol. Forecast. Soc. Change* **2018**, *13*, 2–17. [CrossRef]
73. Orzes, G.; Rauch, S.; Poklemba, R. Industry 4.0 Implementation Barriers in Small and Medium Sized Enterprises: A Focus Group Study. In Proceedings of the IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Bangkok, Thailand, 16–19 December 2018; Volume 12, pp. 1348–1352. [CrossRef]
74. Nazir, O.; Islam, J.U. Effect of CSR activities on meaningfulness, compassion, and employee engagement: A sense-making theoretical approach. *Int. J. Hosp. Manag.* **2020**, *15*, 90–98. [CrossRef]
75. Nagypal, N.C. Corporate social responsibility of Hungarian SMEs with good environmental practices. *J. East Eur. Manag. Stud.* **2014**, *19*, 327–347. [CrossRef]
76. Richter, N.F.; Cepeda, G.; Roldan, J.L.; Ringle, C.M. European management research using partial least squares structural equation modelling (PLS-SEM). *Eur. Manag. J.* **2016**, *34*, 589–597. [CrossRef]
77. Bankowska, K.; Ferrando, A.; Garcia, A. Access to finance for small and medium-sized enterprises since the financial crisis: Evidence from survey data. *ECB Econ. Bull.* **2020**, *4*, 5–12.
78. Silvestre, W.J.; Fonseca, A.; Morioka, S.N. Strategic sustainability integration: Merging management tools to support business model decisions. *Bus. Strategy Environ.* **2022**, *31*, 2052–2067. [CrossRef]
79. Golden, D.; Johnson, T. AI-augmented cybersecurity: How cognitive technologies can address the cyber workforce shortage. *Deloitte Rev.* **2018**, *22*, 47–55.
80. Souto, J.E. Organizational creativity and sustainability-oriented innovation as drivers of sustainable development: Overcoming firms' economic, environmental, and social sustainability challenges. *J. Manuf. Technol. Manag.* **2022**, *33*, 805–826. [CrossRef]
81. Bondarevaa, I.; Zatrochova, M. Financial support for the development of SMEs in the Slovak Republic. *Procedia Soc. Behav. Sci.* **2014**, *1*, 541–548. [CrossRef]
82. Karafolas, S.; Wozniak, M. Financial Sources and Instruments for Public Grants and Financial Facilities of SMEs in EU. *Int. Sch. Sci. Res. Innov.* **2014**, *8*, 2590–2596.
83. Valaskova, K.; Gajdosikova, D.; Kramaric, T.P. How Important Is the Business Environment for the Performance of Enterprises? Case Study of Selected European Countries. *Cent. Eur. Bus. Rev.* **2022**, *11*, 85–110. [CrossRef]
84. Mitan, A.; Siekelova, A.; Rusu, M.; Rovnak, M. Value-based management: A case study of Visegrad Four countries. *Ekon. Manaz. Spektrum* **2021**, *15*, 87–98. [CrossRef]
85. Gajdosikova, D.; Valaskova, K.; Kliestik, T.; Machova, V. COVID-19 Pandemic and Its Impact on Challenges in the Construction Sector: A Case Study of Slovak Enterprises. *Mathematics* **2022**, *10*, 3130. [CrossRef]
86. Haywood, L.K. Putting risk management into the corporate sustainability context. *Soc. Responsib. J.* **2021**, *12*, 24–29. [CrossRef]
87. Krykavskyy, A.; Pokhylchenko, O.; Hayvanovych, N. Supply chain development drivers in industry 4.0 in Ukrainian enterprises. *Oeconomia Copernic.* **2019**, *10*, 273–290. [CrossRef]
88. Metzker, Z.; Marousek, J.; Zvarikova, K.; Hlawiczka, R. The perception of SMEs bankruptcy concerning CSR implementation. *Int. J. Entrep. Knowl.* **2021**, *9*, 85–95. [CrossRef]
89. Nagy, M.; Lăzăroiu, G. Computer Vision Algorithms, Remote Sensing Data Fusion Techniques, and Mapping and Navigation Tools in the Industry 4.0-based Slovak Automotive Sector. *Mathematics* **2022**, *10*, 3543. [CrossRef]
90. Valaskova, K.; Nagy, M.; Zabojnik, S.; Lăzăroiu, G. Industry 4.0 Wireless Networks and Cyber-Physical Smart Manufacturing Systems as Accelerators of Value-Added Growth in Slovak Exports. *Mathematics* **2022**, *10*, 2452. [CrossRef]
91. Shaw, S.; Rowland, Z.; Machova, V. Internet of Things Smart Devices, Sustainable Industrial Big Data, and Artificial Intelligence-based Decision-Making Algorithms in Cyber-Physical System-based Manufacturing. *Econ. Manag. Financ. Mark.* **2021**, *16*, 106–116. [CrossRef]
92. Andronie, M.; Lăzăroiu, G.; Iatagan, M.; Uță, C.; Ștefănescu, R.; Cocoșatu, M. Artificial Intelligence-Based Decision-Making Algorithms, Internet of Things Sensing Networks, and Deep Learning-Assisted Smart Process Management in Cyber-Physical Production Systems. *Electronics* **2021**, *10*, 2497. [CrossRef]
93. Andronie, M.; Lăzăroiu, G.; Ștefănescu, R.; Uță, C.; Dijmărescu, I. Sustainable, Smart, and Sensing Technologies for Cyber-Physical Manufacturing Systems: A Systematic Literature Review. *Sustainability* **2021**, *13*, 5495. [CrossRef]

94. Stehel, V.; Bradley, C.; Suler, P.; Bilan, S. Cyber-Physical System-based Real-Time Monitoring, Industrial Big Data Analytics, and Smart Factory Performance in Sustainable Manufacturing Internet of Things. *Econ. Manag. Financ. Mark.* **2021**, *16*, 42–51. [CrossRef]
95. Sierra-Perez, J.; Teixeira, J.G.; Romero-Piqueras, C.; Patricio, L. Designing sustainable services with the ECO-Service design method: Bridging user experience with environmental performance. *J. Clean. Prod.* **2021**, *305*, 127228. [CrossRef]
96. Zvarikova, K.; Rowland, M.; Krulicky, T. Sustainable Industry 4.0 Wireless Networks, Smart Factory Performance, and Cognitive Automation in Cyber-Physical System-based Manufacturing. *J. Self Gov. Manag. Econ.* **2021**, *9*, 9–20. [CrossRef]
97. Gibson, P.; Macek, J. Sustainable Industrial Big Data, Automated Production Processes, and Cyber-Physical System-based Manufacturing in Smart Networked Factories. *J. Self Gov. Manag. Econ.* **2021**, *9*, 22–34. [CrossRef]
98. Andronie, M.; Lăzăroiu, G.; Iatagan, M.; Hurloiu, I.; Dijmărescu, I. Sustainable Cyber-Physical Production Systems in Big Data-Driven Smart Urban Economy: A Systematic Literature Review. *Sustainability* **2021**, *13*, 751. [CrossRef]
99. Suler, P.; Palmer, L.; Bilan, S. Internet of Things Sensing Networks, Digitized Mass Production, and Sustainable Organizational Performance in Cyber-Physical System-based Smart Factories. *J. Self Gov. Manag. Econ.* **2021**, *9*, 42–51. [CrossRef]
100. Lăzăroiu, G.; Pera, A.; Ștefănescu-Mihăilă, R.O.; Mircică, N.; Neguriță, O. Can Neuroscience Assist Us in Constructing Better Patterns of Economic Decision-Making? *Front. Behav. Neurosci.* **2017**, *11*, 188. [CrossRef]
101. Blake, R.; Michalkova, L.; Bilan, Y. Robotic Wireless Sensor Networks, Industrial Artificial Intelligence, and Deep Learning-assisted Smart Process Planning in Sustainable Cyber-Physical Manufacturing Systems. *J. Self Gov. Manag. Econ.* **2021**, *9*, 48–61. [CrossRef]
102. Andronie, M.; Lăzăroiu, G.; Ștefănescu, R.; Ionescu, L.; Cocoșatu, M. Neuromanagement decision-making and cognitive algorithmic processes in the technological adoption of mobile commerce apps. *Oeconomia Copernic.* **2021**, *12*, 1033–1062. [CrossRef]
103. Markauskas, M.; Baliute, A. Technological progress spillover effect in Lithuanian manufacturing industry. *Equilib. Q. J. Econ. Econ. Policy* **2021**, *16*, 783–806. [CrossRef]
104. Pelau, C.; Dabija, D.-C.; Ene, I. What Makes an AI Device Human-Like? The Role of Interaction Quality, Empathy and Perceived Psychological Anthropomorphic Characteristics in the Acceptance of Artificial Intelligence in the Service Industry. *Comput. Hum. Behav.* **2021**, *122*, 106855. [CrossRef]
105. Prokop, V.; Kotkova Striteska, M.; Stejskal, J. Fostering Czech firms' innovation performance through efficient cooperation. *Oeconomia Copernic.* **2021**, *12*, 671–700. [CrossRef]
106. Barbu, C.M.; Florea, D.L.; Dabija, D.C.; Barbu, M.C.R. Customer Experience in Fintech. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 1415–1433. [CrossRef]
107. Kljucnikov, A.; Civelek, M.; Fialova, V.; Folvarcna, A. Organizational, local, and global innovativeness of family-owned SMEs depending on firm-individual level characteristics: Evidence from the Czech Republic. *Equilib. Q. J. Econ. Econ. Policy* **2021**, *16*, 169–184. [CrossRef]
108. Kolkova, A.; Kljucnikov, A. Demand forecasting: An alternative approach based on technical indicator Pbands. *Oeconomia Copernic.* **2021**, *12*, 1063–1094. [CrossRef]
109. Lăzăroiu, G.; Ionescu, L.; Andronie, M.; Dijmărescu, I. Sustainability Management and Performance in the Urban Corporate Economy: A Systematic Literature Review. *Sustainability* **2020**, *12*, 7705. [CrossRef]
110. Kliestik, T.; Valaskova, K.; Lăzăroiu, G.; Kovacova, M.; Vrbka, J. Remaining Financially Healthy and Competitive: The Role of Financial Predictors. *J. Compet.* **2020**, *12*, 74–92. [CrossRef]
111. Zvarikova, K.; Frajtova Michalikova, K.; Rowland, M. Retail Data Measurement Tools, Cognitive Artificial Intelligence Algorithms, and Metaverse Live Shopping Analytics in Immersive Hyper-Connected Virtual Spaces. *Linguist. Philos. Investig.* **2022**, *21*, 9–24. [CrossRef]
112. Kliestik, T.; Vochozka, M.; Vasić, M. Biometric Sensor Technologies, Visual Imagery and Predictive Modeling Tools, and Ambient Sound Recognition Software in the Economic Infrastructure of the Metaverse. *Rev. Contemp. Philos.* **2022**, *21*, 72–88. [CrossRef]
113. Peters, M.A. A Post-Marxist Reading of the Knowledge Economy: Open Knowledge Production, Cognitive Capitalism, and Knowledge Socialism. *Anal. Metaphys.* **2022**, *21*, 7–23. [CrossRef]
114. Novak, A.; Novak Sedlackova, A.; Vochozka, M.; Popescu, G.H. Big Data-driven Governance of Smart Sustainable Intelligent Transportation Systems: Autonomous Driving Behaviors, Predictive Modeling Techniques, and Sensing and Computing Technologies. *Contemp. Read. Law Soc. Justice* **2022**, *14*, 100–117. [CrossRef]
115. Kovacova, M.; Novak, A.; Machova, V.; Carey, B. 3D Virtual Simulation Technology, Digital Twin Modeling, and Geospatial Data Mining in Smart Sustainable City Governance and Management. *Geopolit. Hist. Int. Relat.* **2022**, *14*, 43–58. [CrossRef]
116. Durana, P.; Krulicky, T.; Taylor, E. Working in the Metaverse: Virtual Recruitment, Cognitive Analytics Management, and Immersive Visualization Systems. *Psychosociol. Issues Hum. Resour. Manag.* **2022**, *10*, 135–148. [CrossRef]
117. Valaskova, K.; Machova, V.; Lewis, E. Virtual Marketplace Dynamics Data, Spatial Analytics, and Customer Engagement Tools in a Real-Time Interoperable Decentralized Metaverse. *Linguist. Philos. Investig.* **2022**, *21*, 105–120. [CrossRef]
118. Zauskova, A.; Miklencicova, R.; Popescu, G.H. Visual Imagery and Geospatial Mapping Tools, Virtual Simulation Algorithms, and Deep Learning-based Sensing Technologies in the Metaverse Interactive Environment. *Rev. Contemp. Philos.* **2022**, *21*, 122–137. [CrossRef]

119. Ionescu, L. Big Data Analytics Tools and Machine Learning Algorithms in Cloud-based Accounting Information Systems. *Anal. Metaphys.* **2021**, *20*, 102–115. [CrossRef]
120. Valaskova, K.; Horak, J.; Lăzăroiu, G. Socially Responsible Technologies in Autonomous Mobility Systems: Self-Driving Car Control Algorithms, Virtual Data Modeling Tools, and Cognitive Wireless Sensor Networks. *Contemp. Read. Law Soc. Justice* **2022**, *14*, 172–188. [CrossRef]
121. Zvarikova, K.; Horak, J.; Downs, S. Digital Twin Algorithms, Smart City Technologies, and 3D Spatio-Temporal Simulations in Virtual Urban Environments. *Geopolit. Hist. Int. Relat.* **2022**, *14*, 139–154. [CrossRef]
122. Watson, R. Tradeable Digital Assets, Immersive Extended Reality Technologies, and Blockchain-based Virtual Worlds in the Metaverse Economy. *Smart Gov.* **2022**, *1*, 7–20. [CrossRef]
123. Nica, E.; Poliak, M.; Popescu, G.H.; Pârvu, I.-A. Decision Intelligence and Modeling, Multisensory Customer Experiences, and Socially Interconnected Virtual Services across the Metaverse Ecosystem. *Linguist. Philos. Investig.* **2022**, *21*, 137–153. [CrossRef]
124. Zvarikova, K.; Machova, V.; Nica, E. Cognitive Artificial Intelligence Algorithms, Movement and Behavior Tracking Tools, and Customer Identification Technology in the Metaverse Commerce. *Rev. Contemp. Philos.* **2022**, *21*, 171–187. [CrossRef]
125. Rogers, S.; Zvarikova, K. Big Data-driven Algorithmic Governance in Sustainable Smart Manufacturing: Robotic Process and Cognitive Automation Technologies. *Anal. Metaphys.* **2021**, *20*, 130–144. [CrossRef]
126. Balica, R.-Ș.; Cuțitoi, A.-C. Ethical Artificial Intelligence in Smart Mobility Technologies: Autonomous Driving Algorithms, Geospatial Data Mining Tools, and Ambient Sound Recognition Software. *Contemp. Read. Law Soc. Justice* **2022**, *14*, 64–81. [CrossRef]
127. Zvarikova, K.; Cug, J.; Hamilton, S. Virtual Human Resource Management in the Metaverse: Immersive Work Environments, Data Visualization Tools and Algorithms, and Behavioral Analytics. *Psychosociol. Issues Hum. Resour. Manag.* **2022**, *10*, 7–20. [CrossRef]
128. Kliestik, T.; Novak, A.; Lăzăroiu, G. Live Shopping in the Metaverse: Visual and Spatial Analytics, Cognitive Artificial Intelligence Techniques and Algorithms, and Immersive Digital Simulations. *Linguist. Philos. Investig.* **2022**, *21*, 187–202. [CrossRef]
129. Grupac, M.; Lăzăroiu, G. Image Processing Computational Algorithms, Sensory Data Mining Techniques, and Predictive Customer Analytics in the Metaverse Economy. *Rev. Contemp. Philos.* **2022**, *21*, 205–222. [CrossRef]
130. Blake, R.; Frajtova Michalikova, K. Deep Learning-based Sensing Technologies, Artificial Intelligence-based Decision-Making Algorithms, and Big Geospatial Data Analytics in Cognitive Internet of Things. *Anal. Metaphys.* **2021**, *20*, 159–173. [CrossRef]
131. Pera, A. The Moral Decision-Making Capacity of Autonomous Mobility Technologies: Route Planning Algorithms, Simulation Modeling Tools, and Intelligent Traffic Monitoring Systems. *Contemp. Read. Law Soc. Justice* **2022**, *14*, 136–153. [CrossRef]
132. Popescu, G.H.; Ciurlău, C.F.; Stan, C.I.; Băcănoiu (Văduva), C.; Tănase (Veisa), A. Virtual Workplaces in the Metaverse: Immersive Remote Collaboration Tools, Behavioral Predictive Analytics, and Extended Reality Technologies. *Psychosociol. Issues Hum. Resour. Manag.* **2022**, *10*, 21–34. [CrossRef]
133. Kral, P.; Janoskova, K.; Potcovaru, A.-M. Digital Consumer Engagement on Blockchain-based Metaverse Platforms: Extended Reality Technologies, Spatial Analytics, and Immersive Multisensory Virtual Spaces. *Linguist. Philos. Investig.* **2022**, *21*, 252–267. [CrossRef]
134. Valaskova, K.; Horak, J.; Bratu, S. Simulation Modeling and Image Recognition Tools, Spatial Computing Technology, and Behavioral Predictive Analytics in the Metaverse Economy. *Rev. Contemp. Philos.* **2022**, *21*, 239–255. [CrossRef]
135. Kovacova, M.; Oláh, J.; Popp, J.; Nica, E. The Algorithmic Governance of Autonomous Driving Behaviors: Multi-Sensor Data Fusion, Spatial Computing Technologies, and Movement Tracking Tools. *Contemp. Read. Law Soc. Justice* **2022**, *14*, 27–45. [CrossRef]
136. Kliestik, T.; Poliak, M.; Popescu, G.H. Digital Twin Simulation and Modeling Tools, Computer Vision Algorithms, and Urban Sensing Technologies in Immersive 3D Environments. *Geopolit. Hist. Int. Relat.* **2022**, *14*, 9–25. [CrossRef]
137. Kral, P.; Janoskova, K.; Dawson, A. Virtual Skill Acquisition, Remote Working Tools, and Employee Engagement and Retention on Blockchain-based Metaverse Platforms. *Psychosociol. Issues Hum. Resour. Manag.* **2022**, *10*, 92–105. [CrossRef]
138. Blake, R. Metaverse Technologies in the Virtual Economy: Deep Learning Computer Vision Algorithms, Blockchain-based Digital Assets, and Immersive Shared Worlds. *Smart Gov.* **2022**, *1*, 35–48. [CrossRef]
139. Durana, P.; Valaskova, K. The Nexus between Smart Sensors and the Bankruptcy Protection of SMEs. *Sensors* **2022**, *22*, 8671. [CrossRef]
140. Balcerzak, A.P.; Nica, E.; Rogalska, E.; Poliak, M.; Kliestik, R.; Sabie, O.M. Blockchain Technology and Smart Contracts in Decentralized Governance Systems. *Adm. Sci.* **2022**, *12*, 96. [CrossRef]
141. Valaskova, K.; Vochozka, M.; Lăzăroiu, G. Immersive 3D Technologies, Spatial Computing and Visual Perception Algorithms, and Event Modeling and Forecasting Tools on Blockchain-based Metaverse Platforms. *Anal. Metaphys.* **2022**, *21*, 74–90. [CrossRef]
142. Zvarikova, K.; Horak, J.; Bradley, P. Machine and Deep Learning Algorithms, Computer Vision Technologies, and Internet of Things-based Healthcare Monitoring Systems in COVID-19 Prevention, Testing, Detection, and Treatment. *Am. J. Med. Res.* **2022**, *9*, 145–160. [CrossRef]
143. Nemțeanu, S.M.; Dabija, D.C.; Gazzola, P.; Vatamanescu, E.M. Social Reporting Impact on Non-Profit Stakeholder Satisfaction and Trust during the COVID-19 Pandemic on an Emerging Market. *Sustainability* **2022**, *14*, 13153. [CrossRef]

144. Zvarikova, K.; Rowland, Z.; Nica, E. Multisensor Fusion and Dynamic Routing Technologies, Virtual Navigation and Simulation Modeling Tools, and Image Processing Computational and Visual Cognitive Algorithms across Web3-powered Metaverse Worlds. *Anal. Metaphys.* **2022**, *21*, 125–141. [CrossRef]
145. Koveschnikov, A.; Dabija, D.C.; Inkpen, A.; Vătămănescu, E.M. Not Running Out of Steam after 30 Years: The Enduring Relevance of Central and Eastern Europe for International Management Scholarship. *J. Int. Manag.* **2022**, *28*, 100973. [CrossRef]
146. Kovacova, M.; Horak, J.; Popescu, G.H. Haptic and Biometric Sensor Technologies, Deep Learning-based Image Classification Algorithms, and Movement and Behavior Tracking Tools in the Metaverse Economy. *Anal. Metaphys.* **2022**, *21*, 176–192. [CrossRef]
147. Vătămănescu, E.-M.; Brătianu, C.; Dabija, D.-C.; Popa, S. Capitalizing Online Knowledge Networks: From Individual Knowledge Acquisition towards Organizational Achievements. *J. Knowl. Manag.* **2022**. *ahead of print*. [CrossRef]
148. Durana, P.; Musova, Z.; Cuțitoi, A.-C. Digital Twin Modeling and Spatial Awareness Tools, Acoustic Environment Recognition and Visual Tracking Algorithms, and Deep Neural Network and Vision Sensing Technologies in Blockchain-based Virtual Worlds. *Anal. Metaphys.* **2022**, *21*, 261–277. [CrossRef]
149. Stone, D.; Michalkova, L.; Machova, V. Machine and Deep Learning Techniques, Body Sensor Networks, and Internet of Things-based Smart Healthcare Systems in COVID-19 Remote Patient Monitoring. *Am. J. Med. Res.* **2022**, *9*, 97–112. [CrossRef]
150. Crișan-Mitra, C.; Stanca, L.; Dabija, D.C. Corporate Social Performance: An Assessment Model on an Emerging Market. *Sustainability* **2020**, *12*, 4077. [CrossRef]
151. Schoeneman, J.; Zhou, B.L.; Desmarais, B.A. Complex dependence in foreign direct investment: Network theory and empirical analysis. *Political Sci. Res. Methods* **2022**, *12*, 243–259. [CrossRef]