PILLARS IN THE MAKING, INDUSTRY 4.0 ON THE HORIZON

Engin Akman
Independent Researcher
Mechanicsburg, PA, USA
usenakman@gmail.com

Abdullah Karaman
College of Engineering and Technology,
American University of the Middle East,
Kuwait
Abdullah.Karaman@aum.edu.kw

ABSTRACT

Industry 4.0 (I4.0) marks a new era in manufacturing and has attracted notable attention from practitioners and researchers. Current production processes are being transformed towards interconnecting the elements of manufacturing systems as a result of digitization. Adopting new technologies is an indispensable practice to compete and sustain business concerns. In this paper, the Analytical Hierarchy Process (AHP), a multi-criteria decision-making methodology, is employed to evaluate and weigh the nine pillars that are the building blocks of an I4.0 system. The assessment model suggests three dimensions, nine pillars, and thirty-four sub-pillars which are evaluated by fourteen I4.0 professionals responding to a pairwise questionnaire. The results are important as they reflect the opinions of the professionals and can help define strategies for companies investing in I4.0 technologies by elucidating the relative impacts of factors in an I4.0 environment.

Keywords: Industry 4.0; nine pillars; Cyber-Physical Systems; Industrial Internet of Things; Multi-Criteria Decision-Making; AHP

1. Introduction

Breakthroughs in industry are defined as industrial revolutions and it is accepted that civilization has witnessed four such revolutions. The energy resources and production tools employed in manufacturing, as well as business processes, define the industrial eras. It is widely presumed that the first industrial revolution started in the late 1700s when steam energy was introduced to provide powerful machines. The entry of electrical energy and mass production in manufacturing marked the start of Industry 2.0 about a century later. The inclusion of computers, electronics, and automation in the 1970s is considered the start of the third industrial revolution (Rüßmann et al., 2015). There is no consensus among researchers about the specific start and end dates of each of the industrial revolutions. The authors think there is only a beginning of an industrial

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

revolution, as the inventions of the earlier periods are still in use in one form or another. A distinguishing quality of the revolutions is that they are disruptive.

Industry 4.0 (I4.0) describes a production style in which the internet, connected networks, automation, and digitization rise giving way to a cyber-revolution, causing systems invented during the first three industrial revolutions to become smart. I4.0 was first articulated at the Hannover Fair in 2011 (Vogel-Heuser & Hess, 2016) and has been changing the pace of manufacturing in the last decade. In this new chapter of the industrial revolution, businesses plan to integrate industrial assets acquired into digital platforms and the internet to make them more intelligent and interactive, thus, creating cyber-physical systems (CPS; Hermann et al., 2016). I4.0 enables physical systems to learn, think, manage, process, communicate, decide, and optimize as a result of advanced technologies (Rüßmann et al., 2015). An operating I4.0 manufacturing system can be achieved by smart and autonomous systems supported by big data and machine learning. I4.0 enables connected and communicating computers to make decisions with limited human participation (Marr, 2016). Though there are no identifying standards for the elements, processes, and interactions, there are initiatives to define the standards, particularly in the US and Germany (Rüßmann et al., 2015). A network of CPSs and the Internet of Things (IoT) make effective use of accumulated data and turn that data into results creating a principle summarized as “optimize yourself, communicate and help optimize the rest”.

The volumes of data are exploding, and more data has been created in two years than in the entire history of humanity. Less than 0.5% of the data is used or analyzed indicating the scale of the potential as data is produced at a greater rate than the industries absorb and consume it (Marr, 2015). Big data is accumulated by about 22 billion connected devices (Mercer, 2019). The Industrial IoT (IIoT) is being used in more machines and objects, and processes such as procurement, design, production, and maintenance of companies will be further automated.

IIoT, CPS, and big data are major enablers of the transition to smart manufacturing or I4.0, but the concept is more sophisticated and has numerous components. Most researchers agree that the components can be grouped into, though not limited to, the following nine pillars: big data and analytics, autonomous robots, simulation, horizontal and vertical system integration, the industrial internet of things, cybersecurity, the cloud, additive manufacturing and augmented reality (Alcácer & Cruz-Machado, 2019; Bahrin et al., 2016; Motyl et al., 2017; Rüßmann et al., 2015; Vaidya et al., 2018; Wang & Wang, 2016). Each pillar requires a thorough understanding and sound infrastructure starting from the conceptual design to the after-sales services. The combination of all of the pillars leads to a complete transformation to I4.0. In fact, each pillar has a great potential impact on the production systems and sophisticated nature that make it harder for practitioners and academics to handle. This study aims to investigate the pillars and their components that can enable a benchmark for professionals performing a gap analysis and help direct investments in building I4.0 processes.

Many of the world's leading industrial nations have been investing in national initiatives to develop advanced manufacturing, innovation, and design to keep up with I4.0 trends in the last decade. For example, the investment projects to adopt I4.0 technologies in 2015-2020 exceeded 40 billion euros in Germany (Oztemel & Gursev, 2020). The investments have been driven by the vision to achieve intelligent factories and smart manufacturing augmented by internet technologies (Zhong et al., 2017). New business processes are mostly aimed at increased flexibility in manufacturing to satisfy the ever-changing and customized customer demands (Alcácer & Cruz-Machado, 2019) with pressure to meet strict quality and delivery time requirements.

Despite the aspiration to integrate innovative concepts into current practices, most businesses lack strategy, knowledge, and skills. Recent research conducted with 2,029 C-Suite leaders from 19 countries showed that while 70% believe switching to I4.0 technologies is an obligation for long-term success, only 10% of the executives have a clear and robust roadmap paving the way to I4.0. About 60% think they are in the stage of understanding the skills needed for the transition period and only 20% agree their institutions have the necessary skills in the I4.0 era (Deloitte Development LLC, 2020). Investments in I4.0 technologies are only possible after the correct strategy is defined by competent corporate executives (Luthra & Mangla, 2018). Notwithstanding the fast pace of technological innovation and the increasing amount of research carried out by practitioners and academics, the I4.0 paradigm is far from maturity. Academic studies focusing on the concepts, definitions, components, skills, and relationships among them can help build a roadmap and assist in implementation of I4.0. Our title "Pillars in the making, Industry 4.0 is on the horizon" addresses the gap in the literature and suggests that there is a long way to go. This research contributes building the concept of I4.0 from the viewpoint of the industrial professional focusing on the criteria that ensure the design, realization, and development of I4.0.

Defining a comprehensive configuration for I4.0 that is adaptable across various industries is crucial since the components of the new manufacturing systems will be highly independent and incorporated. In addition, there are very diverse application alternatives introduced by technology developing companies (Contreras-Masse et al., 2020). A conceptual structure showing the hierarchy of the elements can help both practitioners and academics in the making of I4.0. We adopted a taxonomic method, which has contributed to the development of science since early times, to define I4.0. The study is aimed at disentangling the concept and helping design a roadmap for the new industrial era for practitioners, academics, and policymakers.

In this paper, the Analytical Hierarchy Process (AHP), a multi-criteria decision-making (MCDM) methodology, is used to evaluate and rank the nine pillars that are the building blocks of I4.0. The assessment model considers three dimensions, nine pillars, and thirty-four sub-pillars which are evaluated by fourteen I4.0 professionals replying to a pairwise questionnaire. The results of the study are valuable in putting forth the ranking of the pillars and the alignment of projects in transforming to I4.0.

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

The article is structured as follows. The literature review focuses on the literature defining I4.0 and the nine pillars. The two-phase research methodology is explained in the following section. Results are explained in the findings and discussion section. The conclusion explains the contribution of the article, the limitations, and further research topics motivated by the results.

2. Literature review

Academia as well as industries focus on I4.0 as it is a decisive topic for the future of manufacturing. It is shaping many different kinds of industries, supply chains, human resources, investments, education, training, and society (Bai et al., 2020). However, there is a substantial lack of comprehension about I4.0 technologies and their interactions (Kamble et al., 2018). The companies adopting new technologies enjoy increasing productivity and quality, higher customer satisfaction, and competitiveness (Rüßmann et al., 2015). Better results are expected due to the improvements recorded in production, financial performance, market share, supply chain management, product lifecycle management, talent management, and business models (Prause, 2015; Rosa et al., 2020). In addition to I4.0 being an industrial revolution, the gap in knowledge and the advantages of the I4.0 innovations are major reasons both researchers and practitioners are attracted to this topic (Liao et al., 2017; Rosa et al., 2020).

Müller et al. (2018) suggested that the current status of a company regarding I4.0 adoption falls into one of the four following groups: craft manufacturers (do not have any plan to switch to I4.0), introductory phase planners (trying to embed new systems), I4.0 users (implemented some of the pillars to a certain degree), and full-scale adopters. The overwhelming majority of corporations, excluding the first group, are consumers of I4.0 technologies which show the importance of literature that disentangles the concept into absorbable and adaptable elements.

I4.0 solutions can help solve problems in different spheres as well as industries. For example, the applications adopted in the healthcare sector have enabled effective methods for frontline workers in the COVID-19 pandemic (Javaid et al., 2020).

Da Silva et al. (2019) focused on technology transfer (TT) in importing and integrating advanced technologies into the functional members of manufacturing processes within the framework of I4.0. Collaboration instead of competition and “real-time visibility” in the supply chain will be the major characteristics of TT. To contribute to the understanding and delivery of technology in building I4.0 infrastructure, more research will be needed. Our study has the potential to guide professionals engaged in the TT process.

Attempts to classify the technologies to build a taxonomy, identifying the challenges and solutions, defining standards and scales to explain the outcomes for both digital and physical assets are the main areas of research in the I4.0 literature (Dalenogare et al., 2018; Luthra & Mangla, 2018; Oztemel & Gursev, 2020). MCDM methods have been used in the I4.0 literature to evaluate the concept from different points of view. MCDM, particularly the AHP, which can bring conflicting opinions of experts together is a suitable method for the I4.0 paradigm as maturity level, utilization and understanding of each pillar is at a different stage and the adoption rates of I4.0 technologies vary significantly across industrial sectors and sizes of corporations (Calabrese et al., 2020; Frank et al., 2019). Frank et al. (2019) addressed the gaps in understanding of I4.0 technologies and adoption patterns of manufacturing companies. Luthra and Mangla (2018) focused on the criteria of I4.0 implementation in supply chain sustainability employing AHP and rank organizational challenges ahead of technological challenges for success. Erdogan et al. (2018) used AHP-VIKOR to support the selection of useful strategies in the I4.0 transformation employing factors like human resources, information systems, business models, and standardization. Bai et al. (2020) developed hybrid MCDM utilizing a hesitant fuzzy set, cumulative prospect theory, and VIKOR assessing the priority of I4.0 technologies from a sustainability perspective. Contreras-Masse et al. (2020) proposed PROMETHEE-II as an MCDM to select IIoT platforms employed in I4.0 manufacturing. Singh et al. (2018) employed the AHP methodology to define and rank the impact of success factors in I4.0 realization.

Adapting the technology infrastructure and each pillar according to company requirements combined with training of users enables transforming the processes into an operating I4.0 environment (Rüßmann et al., 2015), which encompasses high digitalization, smart manufacturing, and inter and intra-company connectivity (Müller et al., 2018).

2.1 Big data and analytics

Of the nine components, "big data" is the engine of I4.0 as the development is realized by processing this data. The huge volume of data is not crucial as conceived, but the feasibility and quality of the data are crucial since the results depend on the processing of the relevant data. The term “big data” was first used by Michael Cox and David Ellsworth at the Proceedings of the IEEE 8th conference on Visualization in 1997 (Press, 2013):

> *“Visualization provides an interesting challenge for computer systems: data sets are generally quite large, taxing the capacities of main memory, local disk, and even remote disk. We call this the problem of big data. When data sets do not fit in main memory (in core), or when they do not fit even on local disk, the most common solution is to acquire more resources.”*

The concept might have been expressed in other reports or scholarly research even years ago, but we want to highlight that the very first users of the concept perceived it as a “problem” and the “implied” need for cloud computing as “local disk” is incompetent. High volume, variety, and velocity are typical features of big data (Kaur & Singh, 2018), and technologies akin to optical image recognition which can retrieve a certain word in millions of scanned pages enable the usage of big data (Vrochidis et al., 2010). Similarly, data is produced in production facilities, workstations, machinery, maintenance units, vehicles, robots, power plants, supply chains, marketing, and after-sales efforts, etc. in

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

millions of lines as a result of I4.0 technology, and the retrieval and utilization of the right data play an important role in big data. This pillar encompasses 3 main sub-pillars that are elaborated in Table 1 as data management (Bordeleau et al., 2018; Kamble et al., 2018; Lu, 2017; Tao et al., 2018; Vaidya et al., 2018), data mining (Kamble et al., 2018; Lee et al., 2014a; Lee et al., 2014b; Lu, 2017; Tao et al., 2018; Vaidya et al., 2018) and self-organized manufacturing (Lee et al., 2014a; Lee et al., 2014b; Tao et al., 2018; Wang et al., 2016; Wang & Wang, 2016). The sub-pillars or factors that make these features work need to be taken into consideration when designing an effective big data and analytics infrastructure.

2.2 The cloud

Cloud computing technology was created to store, protect, and process constantly growing data, that is, to produce new information from existing data, to reveal complex relationships between data, and to make it available when needed (Oztemel & Gursev, 2020). This big data can be transmitted to people, smart objects, and machines quickly achieving reaction times in milliseconds (Rüssmann et al., 2015). In a cloud, the hardware, software, and real-time data that are used are separated and stored away from the central facilities and are brought together when necessary, often automatically. Obviously, the sine qua non of this new order is the IIoT.

Everything is considered as service in cloud computing and the services include infrastructure, platform, and software (Alcácer & Cruz-Machado, 2019). The infrastructure consists of storage, networking, and virtualization; platforms include operating systems to run the software and are used to develop applications; software applications enable processing data retrieved via interfaces. Access to a cloud can be grouped into four types according to the following access protocols (Alcácer & Cruz-Machado, 2019): public, private, hybrid, and community, which is a specialized part of the public cloud.

2.3 The industrial internet of things

The IIoT is the communication network that enables the communication of physical objects integrated with each other using traditional internet protocols. “Industrial’ and “Things” are crucial concepts in building the IIoT pillar of an I4.0 system. Things can be whatever is used in industrial manufacturing including objects and humans (Alcácer & Cruz-Machado, 2019), and the number of active objects exceeded 22 billion (Mercer, 2019). The IIoT infrastructure enables storing, transmitting, analyzing real-time data, and communicating with the rest of the system elements to optimize the output in terms of lead times, effectiveness, quality, etc. Navigation systems used by billions of people every day are a good example of the importance of obtaining real-time data. These systems allow one to review the route and reach the destination using less time and energy. Utilization of the IIoT is increasing in numerous fields like energy management, marketing, transportation, smart homes, transportation, agriculture, health, and education (Alcácer & Cruz-Machado, 2019; Rüßmann et al., 2015).

The success of the IIoT is dependent on a clear definition of configuration, architectural models, standards, projects, performance indicators, and industrial activities. Four architectural levels are proposed to establish and evaluate the IIoT infrastructure (Alcácer & Cruz-Machado, 2019) starting from the "object" to the end-user. The physical or sensing layer detects and translates the data tags obtained by touching the original source of the data. The network layer performs data transmission from the "object" to the service layer. This level is decisive in the required data to be shared and the destination stations of that data. The third level stores the big data for optimization and decision-making, and the interface level serves as an interface to display data and provide interaction with the system and users. The connections between the four layers can be wired or wireless and additional monitoring provided by a human or other smart device can increase the value of analysis and the level of optimization. Four level automation that is synonymous with the four layers of the IIoT has been used in traditional industries such as steel manufacturing for decades (Gauvreau, 2011), but I4.0 technologies and the internet provided individual stations or objects to store, analyze, decide using "real-time" data and perform actions to reach pre-defined solutions autonomously. The connection and interaction of elements in the system support optimizing the whole value chain.

2.4 Cybersecurity

The connected systems communicating via the IIoT network consisting of embedded electronic systems like RFID, chips, and sensors and physical assets such as objects, machinery, hardware, etc. are called CPSs in the I4.0 literature (Alcácer & Cruz-Machado, 2019). CPSs are central to automation in smart factories as they can plan and operate all production processes with the retrieved data. The traditional automation hierarchy forms a triangle starting with the programmable logic controller (PLC) level to the user-level interface, whereas CPS-based I4.0 automation forms a spider-web with distributed service (Hozdic, 2015). CPSs establish communication between mechanical and electronic components through I4.0 technologies within a network system to create smart manufacturing.

CPSs increase connectivity with global networks using standard internet protocols that make sensitive corporate data, crucial industrial components, and production lines vulnerable to hostile cyber intervention (Rüssmann et al., 2015). The attacks can be originated from an internal or external source (Alcácer & Cruz-Machado, 2019). Corporations are trying to overcome cybersecurity flaws by utilizing secure communications, sophisticated access management of systems, machines, and users as well as cooperating with professional cybersecurity companies. Cybersecurity control points can be categorized into three groups as physical controls regulating access to physical assets, access controls to data resources and communication controls securing the data transmission via networks (Flatt et al., 2016; Kobara, 2016).

2.5 Horizontal and vertical system integration

Horizontal and vertical integration of real-time data flows between all elements of the manufacturing process and is a key concept in a smart factory (Hozdic, 2015). Horizontal integration relates to inter-organizational data transmission beyond the organizational boundaries through all value chains including partners, suppliers, and customers. Vertical integration includes data sharing across intra-organizational processes from conceptual design to manufacturing and after-sales services. End-to-end integration is integration across the organization and different companies incorporating customer demands through the entire product life cycle (Liao et al., 2017). Integration combines the virtual and the real world due to sophisticated IT infrastructure including sensors, actuators, PLCs, manufacturing execution systems, enterprise resource planning systems, machine-to-machine communication (Hozdic, 2015). The nature of complete integration within the framework of I4.0 generates coopetition, which brings cooperation and competition together.

2.6 Autonomous robots

Autonomous robots can make decisions and act on their own in dynamic environments without intervention. They are equipped to collect data and analyze, communicate with connected robots, objects, and operators, move in the workstation and ensure the safety of surroundings (Rüssmann et al., 2015). Embedded systems providing artificial intelligence make these robots smarter. Autonomous robots are used in numerous fields, manufacturing, and services as well as mining and agriculture (Alcácer & Cruz-Machado, 2019). The critical factors of successful operations of autonomous robots are interacting with one another and humans.

2.7 Simulation

Simulation, modeling a concept in the virtual world, has been used in the research and development of products and materials. Innovative I4.0 technologies made it possible to obtain and analyze real-time data from production, processes, machinery, and human behavior (Rüssmann et al., 2015). Engineering simulation helps build optimum design while process simulation helps build optimum processes with fast decision making in manufacturing, maintenance, and customer service, etc. (Alcácer & Cruz-Machado, 2019). Engineering evaluation is defined as off-line simulation and real-time data using modeling for process performance is called on-line simulation (Negahban & Smith, 2014).

Simulation using the current data of an operating system contributes to smart manufacturing considerably as the results such as performance and failures with certain parameters conveyed to similar workstations can help optimize the results of further stations and the next operations of the current station. Obviously, on-line simulation requires sophisticated IT infrastructure with computational efficiency covering all processes of an enterprise. Sub-criteria of simulation infrastructure are virtual prototyping, virtual production, and virtual maintenance, repair, and operations (Kamble et al., 2018; Mourtzis et al., 2014; Qi & Tao, 2018).

2.8 Additive manufacturing (AM)

Producing physical parts from digital data, also known as rapid prototyping, began in the late 1980s (Manfredi et al., 2014). This method used to produce prototypes or sample parts was the first type of 3D printing or additive manufacturing. Today AM technology is used in manufacturing processes with sophisticated methods beyond rapid prototyping technology. AM is defined in the American Society for Testing and Materials (ASTM) 2792-10 standard as (Manfredi et al., 2014):

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

> *"The process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing technologies."*

AM is a smart technology that revolutionized conventional manufacturing methods as customized parts can be manufactured in shorter times with high precision and no waste, molds, or assembly. Aerospace companies were the first to adopt AM technology as it enables complex lightweight designs and decentralized AM systems to reduce shipping costs and stocks (Rüssmann et al., 2015). A conventional AM process includes the geometry design, IT tools and interface development, final design, process forming, and control tools (Alcácer & Cruz-Machado, 2019; Manfredi et al., 2014). ASTM standard F2792 groups AM processes into seven groups as binder jetting, directed energy deposition, material extrusion, material jetting, powder bed fusion, sheet lamination, and VAT polymerization.

2.9 Augmented reality (AR)

In AR technology, the real images are enriched by combining supporting elements such as real-time audio, images, and graphics developed with different digital technologies in their own environment (Oztemel & Gursev, 2020). AR glasses, smart devices or monitors, or other types of imaging tools are often needed. AR has a wide field of applications ranging from education and health to military and tourism. AR is an indispensable part of smart manufacturing and is used in operations such as design, assembly, maintenance, logistics, quality and safety management, and warehousing. AR professionals can perform all necessary operations remotely which speeds up the maintenance, training, and assembly activities in different parts of the world with low-skilled workers (Rüssmann et al., 2015). AR technology has the potential to be significantly developed and used in many different applications from various walks of life (Oztemel & Gursev, 2020). One of the key advantages of AR is the storage and retrieval of high-quality and user-friendly data on company processes like manufacturing, maintenance, safety, and quality which can eliminate paperwork and usage of outdated information (Blanco-Novoa et al., 2018).

AR has five sub-pillars including training, design, manufacturing, operations, and service which are elaborated in Table 1 (Alcácer & Cruz-Machado, 2019; Fraga-Lamas et al., 2018; Kamble et al., 2018; Mourtzis et al., 2017).

3. Research methodology

We followed a two-phase research methodology in this study to determine technology priorities of I4.0. In phase I, we identified the dimensions, pillars, and sub-pillars of the I4.0 technologies with the help of a comprehensive literature review. Then, we formed an experts' panel (EP). The dimensions, pillars, and sub-pillars of the I4.0 technologies were determined through discussions and the support of the EP. In phase II, the priorities of the I4.0 technologies including the dimensions, pillars, and sub-pillars were evaluated via the widely recognized AHP methodology by surveying industry professionals. Figure 1 illustrates the step-by-step research methodology.

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

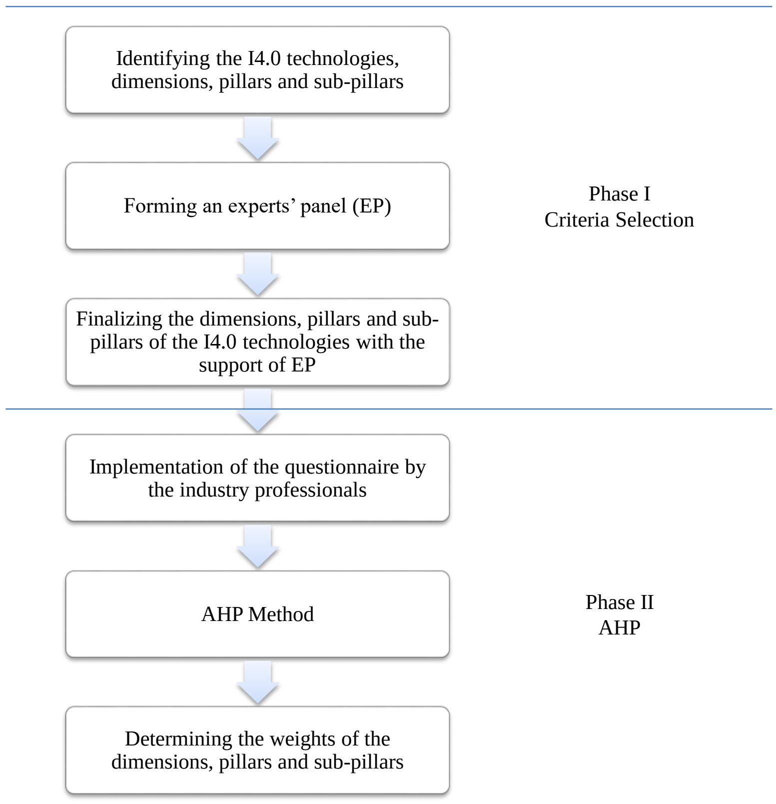

Figure 1 Two-phase research methodology for Industry 4.0 technologies

3.1 Phase I - Criteria selection

The criteria included in the study are a result of combining information from the existing literature and industry experience. The study adopted the nine pillars of I4.0 based on Alcácer and Cruz-Machado (2019), Bahrin et al. (2016), Motyl et al. (2017), Rüßmann et al. (2015), Vaidya et al. (2018), and Wang and Wang (2016). The nine pillars were first grouped into dimensions following the recommendation of the EP as *base technologies*, *smart operations*, and *smart technologies* to make rational and consistent comparisons between similar concepts. The *base technologies* include *the industrial internet of things*, *horizontal and vertical system integration*, *big data and analytics*, *cybersecurity*, and *the cloud*, which provides connectivity and intelligence (Frank, 2019). *Smart operations* includes *simulation* and *augmented reality*. Finally, *smart technologies* includes *autonomous robots* and *additive manufacturing*.

Then, sub-pillars were determined based on the extant literature and the suggestions from the EP. The EP's suggestions helped finalized all the criteria and hierarchy included in the study. The EP was composed of two academics and two industry professionals with more than twenty years of experience. The two researchers authored this study; one of them has substantial expertise in the manufacturing industry, whereas the other one has

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

significant experience in multi-criteria decision-making approaches. As a result, the dimensions, pillars, and sub-pillars were obtained from prior studies and up-to-date industry practices. Final I4.0 dimensions, pillars, sub-pillars, and their explanations are summarized in Table 1 and the structured hierarchy is given in Figure 2 (excluding the sub-pillar level due to the space constraint).

Vol. 13 Issue 2 2021
ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

Table 1
Industry 4.0 dimensions, pillars, and sub-pillars

Dimension	Pillar	Sub-pillar	Explanation	References
Base technologies	The industrial internet of things (IIoT)	Physical layer	Sensors, machines, and products are connected using standard technologies (includes the physical infrastructure)	Alcácer and Cruz-Machado (2019); Gilchrist (2016); Kamble et al. (2018); Lu (2017); Posada et al. (2015); Rüßmann et al. (2015); Sadeghi et al. (2015); Thames and Schaefer (2016); Vaidya et al. (2018); Wan et al. (2016); Wollschlaeger et al. (2017)
		Network layer	Industrial wireless networks transmitting data, commands, etc.	Alcácer and Cruz-Machado (2019); Gilchrist (2016); Lu (2017); Wan et al. (2016); Wollschlaeger et al. (2017)
		Service layer	Stores the big data for optimization and decision-making	Alcácer and Cruz-Machado (2019); Gilchrist (2016); Kamble et al. (2018); Lu (2017); Posada et al. (2015); Thames and Schaefer (2016); Wan et al. (2016); Wollschlaeger et al. (2017)
		Interface layer	Display data and provide interaction with the system and users	Alcácer and Cruz-Machado (2019); Gilchrist (2016); Thames and Schaefer (2016); Wan et al. (2016)
	Horizontal and vertical system integration	Horizontal integration	Horizontal integration across the entire value creation network (from the material flow to the logistics of product life cycle)	Brettel et al. (2014); Dalenogare et al. (2018); Kagermann et al. (2013); Lu (2017); Posada et al. (2015); Rüßmann et al. (2015); Stock and Seliger (2016); Vaidya et al. (2018)

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

Dimension	**Pillar**	**Sub-pillar**	**Explanation**	**References**
		Vertical integration	Vertical integration and networked manufacturing systems (include sensors, actuators, programmable logic controllers, manufacturing execution systems, enterprise resource planning systems, machine-to-machine communication) - integrates product, equipment, and human needs.	Dalenogare et al. (2018); Frank et al. (2019); Kagermann et al. (2013); Lu (2017); Posada et al. (2015); Rüßmann et al. (2015); Stock and Seliger (2016); Vaidya et al. (2018); Weyer et al. (2015)
		End-to-end integration	End-to-end integration across the entire product life cycle.	Brettel et al. (2014); Dalenogare et al. (2018); Kagermann et al. (2013); Posada et al. (2015); Stock and Seliger (2016); Vaidya et al. (2018)
	Big data and analytics	Data management	Collection (data tagging tools), architecture, integration, classification, warehousing (ETL)	Bordeleau et al. (2018); Kamble et al. (2018); Lu (2017); Tao et al. (2018); Vaidya et al. (2018)
		Data mining	Data visualization Real-time machine learning applications include control and monitoring, information-sharing, collaborative decision-making creating operational value. Predictive machine learning applications include prognostics and health management.	Kamble et al. (2018); Lee et al. (2014a); Lee et al. (2014b); Lu (2017); Tao et al. (2018); Vaidya et al. (2018)

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

Dimension	Pillar	Sub-pillar	Explanation	References
		Self-organized manufacturing	Negotiation mechanisms for components, machines, and systems to become self-aware, self-predict, self-compare, self-configure, self-maintain, self-organize, and self-adaptive	Lee et al. (2014a); Lee et al. (2014b); Tao et al. (2018); Wang et al. (2016); Wang and Wang (2016)
	Cybersecurity	Physical controls	Prevents unauthorized access to physical assets	Flatt et al. (2016); Kobara (2016); Rüßmann et al. (2015); Waidner and Kasper (2016);
		Access controls	Restricts unauthorized access to information resources (includes authentication and authorization)	Flatt et al. (2016); He et al. (2016); Kobara (2016); Waidner and Kasper (2016)
		Communication controls	Secures the movement of data across networks	Flatt et al. (2016); He et al. (2016); Kobara (2016); Rüßmann et al. (2015); Waidner and Kasper (2016)
	The cloud	Infrastructure as a service (IaaS)	Infrastructure to run software and store data	Alcácer and Cruz-Machado (2019); Almada-Lobo (2015); Kamble et al. (2018); Lee et al. (2014b); Rüßmann et al. (2015); Vaidya et al. (2018); Wan et al. (2016); Zhou et al. (2015)
		Platform as a service (PaaS)	Platforms to develop applications	Alcácer and Cruz-Machado (2019); Almada-Lobo (2015); Lee et al. (2014b); Rüßmann et al. (2015); Vaidya et al. (2018); Wan et al. (2016); Zhou et al. (2015)
		Software as a service (SaaS)	Software applications to process data	Alcácer and Cruz-Machado (2019); Almada-Lobo (2015); Lee et al. (2014b); Rüßmann et al. (2015); Vaidya et al. (2018); Wan et al. (2016); Zhou et al. (2015)

Dimension	Pillar	Sub-pillar	Explanation	References
Smart operations	Simulation	Virtual prototyping	Product, material, process development	Brettel et al. (2014); Kamble et al. (2018); Mohammad et al. (2021); Mourtzis et al. (2014); Qi and Tao (2018); Rüßmann et al. (2015); Zawadzki and Żywicki (2016)
		Virtual production	Digital twin: design and optimization of cyber-physical production systems	Brettel et al. (2014); Kamble et al. (2018); Lasi et al. (2014); Moreno et al. (2017); Mourtzis et al. (2014); Negri et al. (2017); Qi and Tao (2018); Rodič (2017); Rüßmann et al. (2015); Schleich et al. (2017); Uhlemann et al. (2017); Weyer et al. (2016); Xu et al. (2016)
		Virtual maintenance, repair, and operations (MRO)	Prediction of proactive maintenance	Qi and Tao (2018)
	Augmented reality	Training	Includes job-specific tasks, safety, and security procedures, etc.	Alcácer and Cruz-Machado (2019); Fraga-Lamas et al. (2018); Mourtzis et al. (2017); Posada et al. (2015); Rüßmann et al. (2015)
		Design	Collaborative engineering, error diagnosis, etc.	Alcácer and Cruz-Machado (2019); Fraga-Lamas et al. (2018); Mourtzis et al. (2017); Zhong et al. (2017)
		Manufacturing	Quality assurance, monitoring performance, issuing assembly and maintenance work instructions, tracking, monitoring	Alcácer and Cruz-Machado (2019); Fraga-Lamas et al. (2018); Mourtzis et al. (2017)
		Operations	Augmented interface and operator manuals, heads-up displays, digital product	Alcácer and Cruz-Machado (2019); Fraga-Lamas et al. (2018); Kamble et al. (2018); Rüßmann et al. (2015)

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

Dimension	Pillar	Sub-pillar	Explanation	References
			controls, etc.	
		Service	Remote maintenance/repair guidance, manual and service instructions, service inspections, self-service, etc.	Alcácer and Cruz-Machado (2019); Fraga-Lamas et al. (2018); Kamble et al. (2018); Mourtzis et al. (2017); Rüßmann et al. (2015); Vaidya et al. (2018)
		Sales and marketing	Product display and demos, augmented marketing, etc.	Alcácer and Cruz-Machado (2019); Fraga-Lamas et al. (2018); Mourtzis et al. (2017)
Smart technologies	Autonomous robots	Interaction with one another	Use vision sensors, artificial intelligence, and self-learning to work flexibly with high performance	Bahrin et al. (2016); Dopico et al. (2016); Kamble et al. (2018); Rüßmann et al. (2015); Vaidya et al. (2018);
		Interaction with humans	Work safely hand in hand with humans	Bahrin et al. (2016); Gonzalez et al. (2018); Kamble et al. (2018); Rüßmann et al. (2015); Vaidya et al. (2018);
	Additive manufacturing	Binder jetting	Two materials, the binder (usually in liquid form) and the build material (in powder form) are used along with a print head. The print head moves and deposits alternating layers of the build material and the binding material.	Additive Manufacturing Research Group (2019); Alcácer and Cruz-Machado (2019); International Organization for Standardization (2015); Tofail et al. (2018)

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

Dimension	Pillar	Sub-pillar	Explanation	References
		Directed energy deposition	The laser/electron beam is used to deposit materials by melting.	Additive Manufacturing Research Group (2019); Alcácer and Cruz-Machado (2019); Chong et al. (2018); International Organization for Standardization (2015); Tofail et al. (2018)
		Material extrusion	A nozzle/orifice is used to fuse materials selectively.	Additive Manufacturing Research Group (2019); Alcácer and Cruz-Machado (2019); Chong et al. (2018); International Organization for Standardization (2015); Tofail et al. (2018); Vaidya et al. (2018)
		Material jetting	Material is jetted onto a build platform using either a continuous or drop-on-demand approach.	Additive Manufacturing Research Group (2019); Alcácer and Cruz-Machado (2019); International Organization for Standardization (2015); Tofail et al. (2018)
		Powder bed fusion	The laser/electron beam is used to melt and fuse the material powder together.	Additive Manufacturing Research Group (2019); Alcácer and Cruz-Machado (2019); Chong et al. (2018); International Organization for Standardization (2015); Tofail et al. (2018); Vaidya et al. (2018)
		Sheet lamination	Sheets/ribbons of metals are used to form objects using ultrasonic welding.	Additive Manufacturing Research Group (2019); Alcácer and Cruz-Machado (2019); Chong et al. (2018); International Organization for Standardization (2015); Tofail et al. (2018)
		VAT polymerisation	Uses a vat of liquid photopolymer resin to construct the model layer by layer.	Additive Manufacturing Research Group (2019); Alcácer and Cruz-Machado (2019); Chong et al. (2018); International Organization for Standardization (2015); Tofail et al. (2018)

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

3.2 Phase II – AHP

The assessment of I4.0 technologies is qualitative in its essence and requires a multi-criteria context. Yet, the perception of the experts is even contradictory. From this perspective, the AHP, suggested by Saaty (1980), is a broadly accepted and convenient approach to deal with MCDM (Akman & Dagdeviren, 2018; Karaman & Akman, 2018). The AHP methodology handles a MCDM by structuring a decision hierarchy starting with the goal, criteria, and sub-criteria. An important design constraint for the AHP is the assumption that all the criteria and sub-criteria are independent of each other. In fact, the AHP forms a group decision by assessing the criteria and sub-criteria and finding their relative importance. It combines both qualitative and quantitative factors analytically. In this context, the AHP hierarchy for I4.0 (the goals, dimensions, and pillars) is given in Figure 2 (excluding the sub-pillar level due to the space constraints).

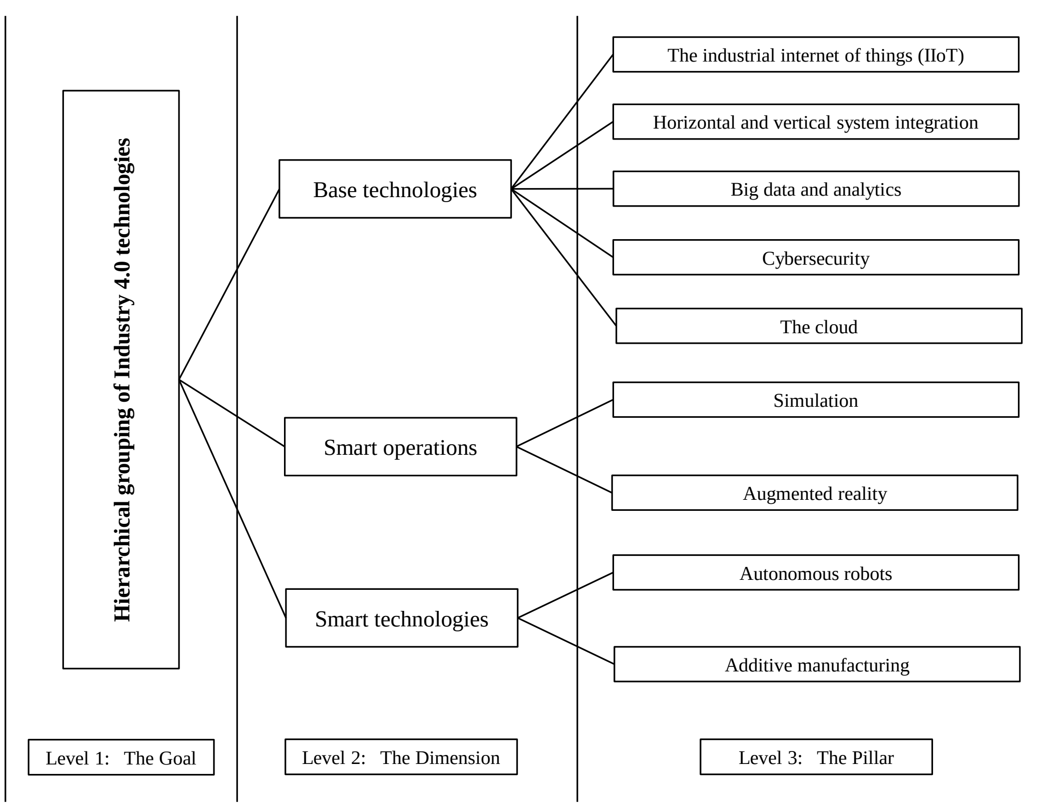

Figure 2 Hierarchy of the AHP model

The next step in the AHP is to determine the priority weights for the determined hierarchy. This is achieved through a pairwise comparison of the dimensions, pillars, and sub-pillars. A standardized scale of the nine levels (as shown in Table 2) is used in the pairwise comparisons.

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

Table 2
AHP scale of the relative importance

Degree of Importance	Definition
1	Equal Importance
3	Moderate Importance
5	Strong Importance
7	Very Strong Importance
9	Absolute Importance

2, 4, 6, 8 are used to articulate intermediate values.

The steps for prioritizing the criteria include summarizing the pairwise comparisons in a pairwise evaluation matrix. The results of n criteria comparisons are stored in a nxn matrix. Let $C = \{C_j \backslash j = 1,2,\cdots,n\}$ represent the set of criteria for I4.0 technologies. The nxn assessment matrix, A, stores the pairwise contrast of the criteria belong to C. The matrix A is written as below in Equation (1):

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{a_{11}} & \boldsymbol{a_{12}} & \cdots & \boldsymbol{a_{1n}} \\ \boldsymbol{a_{21}} & \boldsymbol{a_{22}} & & \boldsymbol{a_{2n}} \\ \vdots & & \ddots & \vdots \\ \boldsymbol{a_{n1}} & \boldsymbol{a_{n2}} & \cdots & \boldsymbol{a_{nn}} \end{bmatrix} \quad (1)$$

Under these circumstances, a_{ij} depicts the numerical value of the pairwise evaluation of criteria i and j for the AHP hierarchy illustrated in Figure 2. a_{ij}'s could assume any value between 1 and 9 as defined in Table 2 and their reciprocals. In particular, values 1 to 9 are used whenever criteria i is more important than criteria j and their reciprocals are used whenever criteria j is more important than criteria i. Other entries of the matrix A are determined by

$a_{ii} = 1,\ a_{ji} = \frac{1}{a_{ij}}$ assuming $a_{ij} \neq 0$.

Next, the AHP normalizes and calculates the relative weights of each matrix A dividing the entries into the columns to the respective column sums. The priority of the elements is determined by letting

$$\boldsymbol{Aw} = \boldsymbol{\lambda_{max} w} \quad (2)$$

where w is the principal eigenvector corresponding to the largest eigenvalue λ_{max}.

A final analysis in the AHP is the consistency check since the pairwise comparison of the criteria of the experts often conflicts and depends on subjective judgments. The consistency check is being conducted in two steps. First, the consistency index (CI) is calculated via

$$\boldsymbol{CI} = \frac{\boldsymbol{\lambda_{max} - n}}{\boldsymbol{n-1}}. \quad (3)$$

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

Second, the consistency ratio (CR) is determined by

$$\boldsymbol{CR} = \frac{\boldsymbol{CI}}{\boldsymbol{RI}}. \tag{4}$$

Certain values of the consistency ratio show acceptable pairwise evaluations. In the current literature, a recognized upper value on CR is 0.1. CR values beyond the upper bound require the process to be repeated or more analysis to be done to improve the consistency of the results (Karaman & Akman, 2018).

3.2.1 Application of AHP

Based on the hierarchy, the authors prepared a questionnaire to assess the relative weights of the dimensions, pillars, and sub-pillars. The questionnaire is shown in the Appendix. The standard AHP scale (provided in Table 2) was used to signify the corresponding importance, 1 representing equal, and 9 symbolizing absolute importance.

The authors adopted a purposive sampling methodology in the selection of fourteen I4.0 professionals. The reliability of the results is highly dependent on the purposive sampling approach (Karaman & Akman, 2018; Öberseder et al., 2013). The professionals experienced in I4.0 in the EP suggested known global decision-makers and opinion leaders. We also used the LinkedIn platform to search for leading practitioners and contacted them. The decision-makers were intentionally chosen based on their expertise and engagement in I4.0 technologies. The professionals had at least ten years of experience in manufacturing, information technology, research and design, quality, and similar domains, while the majority of them had more than twenty-five years of consulting experience in these domains. The survey was sent to seventeen professionals; twelve of them responded and contributed to our research. Two of the EP members also assessed the pairwise comparisons.

The authors analyzed the responses received from the I4.0 professionals using Microsoft Excel. In this step, the AHP weights were obtained by combining the questionnaire answers and computing the geometric average of the pairwise assessments since this creates a group agreement. All the weights of the dimensions, pillars, and sub-pillars were obtained from the authors' own calculations. The CR value of all the assessments was within the acceptable level (less than 0.1).

4. Findings and discussion

The organizational strategy aligned with I4.0 initiatives is key to success in implementation that can be achieved with the support of executive management (Sony & Naik, 2020). This obviously requires the inclusion of technical management to build a straightforward strategy and implementation framework where our results can potentially provide a guide. The nine pillars of I4.0 have gained wide acceptance in the literature and many of the sub-pillars are highlighted in numerous papers as seen in Table 1. We focused on the studies dealing with similar concepts or criteria to explain I4.0 and compare with our study; however, it is hard to completely collate the findings with previous studies as our study adopts a taxonomic method employing the AHP as a

MCDM to rank the factors building an I4.0 environment. To the best of our knowledge, this is the first study to handle I4.0 pillars using our methodology.

The first level of comparison of the research (shown in Table 3) includes *base technologies*, *smart operations*, and *smart technologies*. Frank et al. (2019) suggest that the pattern of I4.0 adoption integrates the methodical implementation of smart (front-end) technologies and base technologies. We separated *smart operations* and proposed them as a third pillar. I4.0 is a fusion of pillar technologies and the path to success requires a sequence of projects ranging from small and gradual to very large and innovative (Prause, 2015; Sony & Naik, 2020). In this manner, a shift of a corporation to I4.0 can be considered as project and change management (Sony & Naik, 2020). The current study asserts that there are three crucial pillars (phases) to achieve the project of a fully operating I4.0 system. The industry professionals view *base technologies* as significantly important followed by *smart operations* and *smart technologies*. Similar to our findings, Frank et al. (2019) report that the implementation of base technologies is challenging for companies. The results indicate that practitioners first focus on the status/maturity of factors given in Table 4 before fully implementing the factors indicated in Tables 5 and 6, respectively.

Table 3
AHP weights and rank of the dimensions

Dimensions	**Weights**	**Rank**
Base technologies	0.547	1
Smart operations	0.287	2
Smart technologies	0.166	3

Adopting I4.0 will lead to colossal cybersecurity challenges as the confident data engendered by I4.0 is streamed through all value chains (He et al., 2016; Sony & Naik, 2020). Smart manufacturing is dependent on cybersecurity maturity as well as operation technologies (Ghobakhloo, 2020). Our study reveals that the protection of data (c*ybersecurity*) is a top priority for industry experts followed by *big data and analytics*, *the cloud*, *IIoT*, and *horizontal and vertical system integration*, respectively. Frank et al. (2019) adopted the four base technology pillars of cloud, IoT, big data, and analytics. Their findings propose that as companies have more mature I4.0 smart manufacturing technologies, they employ more advanced levels of base technologies. The implementation rates of the factors are as follows: IoT (67%), cloud (60%), analytics (60%), and big data (60%) among advanced adopters. The results of Frank et al. (2019) do not resemble our results as they did not include *cybersecurity*. Furthermore, *big data and analytics* is given priority over the enablers *the cloud* and *IIoT* by our experts. The logic behind this result may be the emphasis on the quality of the data collected and the value of analytics for the operations and sustainability of the corporations. One of the experts stated that they got “drowned” in one of their projects as millions of lines of data obtained through tags made it hard to tackle and analyze the data.

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

Table 4
AHP weights and rank of base technologies

Pillars for base technologies	Weights	Rank
IIoT	0.150	4
Horizontal and vertical system integration	0.144	5
Big data and analytics	0.158	2
Cybersecurity	0.397	1
The cloud	0.152	3

Augmented reality, which integrates real operations and *simulation*, is a core technology for building a smart manufacturing environment and a crucial innovation of I4.0 (Oztemel & Gursev, 2020). *Augmented reality* is successfully utilized in fields like maintenance, operations, training, and quality control. Though *simulation* is a more traditional operation employed in industry for decades, our results show that professionals give priority to *simulation*.

Table 5
AHP weights and rank of the smart operations

Pillars for smart operations	Weights	Rank
Simulation	0.670	1
Augmented reality	0.330	2

Autonomous robots and *additive manufacturing* are state-of-the-art technologies and the most distinguishing innovations of I4.0. Though they have similar significance, *autonomous robots* are seen as a more important element of I4.0. *Autonomous robots* represent more conventional technologies enriched with I4.0 technologies while *additive manufacturing* is new in mass or end-user destined production and is still perceived as a tool in the prototyping of a designed part or product. This implies that the experts give more importance to conventional manufacturing processes with *autonomous robots* over *additive manufacturing*.

Table 6
AHP weights and rank of the smart technologies

Pillars for Smart technologies	Weights	Rank
Autonomous robots	0.560	1
Additive manufacturing	0.440	2

Evaluations of dimensions and pillars shed light on the conceptual design and architecture of an I4.0 manufacturing environment. The assessments made so far reflect

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

the approaches of experts to I4.0 in general in defining a roadmap to I4.0. The following parts assessing the sub-pillars focus more on tangible assets in forging the operating processes of I4.0. Hardware, software, equipment, machines, processes, or technologies pertaining to each sub-pillar can be observed at various maturity levels on shop floors of companies that plan to keep up with the pace of I4.0 technologies. The expert views can enable practitioners or researchers to assess the current infrastructure, decide on the gaps, and plan for the next stages in projects and investments.

The *IIoT* consists of various sets of software, hardware, and technologies used in four layers which are connected and integrated via the internet or intranet to support smart production processes. The *IIoT* layers can combine technologies with different maturity levels, but interoperability is the key to successful operation (Alcácer & Cruz-Machado, 2019). The physical layer, the first element to gather raw data from the source where it is produced, is viewed as a sub-pillar with the most significance for the successful operation of IIoT followed by the service layer where data is stored, interface layer which serves as the interface for users and network layer which transmits data between the terminals (Table 7).

Table 7
AHP weights and rank of the IIoT

Sub-pillars for IIoT	**Weights**	**Rank**
Physical layer	0.325	1
Network layer	0.218	4
Service layer	0.230	2
Interface layer	0.227	3

Liao et al. (2017) concluded in their research on I4.0 literature that 20.5% of 479 papers included integration factors, while 45 papers paid attention to vertical, 39 papers to horizontal, and 23 papers to end-to-end integration. Our results showed that the I4.0 professionals view *end-to-end integration* as important which shows more focus on this factor is needed in further studies. *Vertical integration,* which mostly includes IT infrastructure within a company, is seen as the second factor which implies that corporations need to integrate internal processes before they join external value chains (Table 8). Achieving this is particularly important in switching to I4.0 as most companies lack successful internal process integration and some even lack functional units like in the engineering department (Rüssmann et al., 2015).

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

Table 8
AHP weights and rank of the horizontal and vertical system integration

Sub-pillars for horizontal and vertical system integration	**Weights**	**Rank**
Horizontal integration	0.224	3
Vertical integration	0.275	2
End-to-end integration	0.501	1

The hierarchical importance of the *big data and analytics*' sub-pillars is viewed as *data management*, *data mining*, and *self-organized manufacturing*. Most commonly, data is produced in the physical systems, and stored and conveyed within cyber systems. Large volumes of diverse data are produced, and this data is frequently unstructured (Qi & Tao, 2018). For example, data collected in different workstations of a manufacturing facility may contain numerous parameters like temperature, pressure, velocity, thickness, etc. that changes in seconds which makes collecting useful data sophisticated. The *data management* sub-pillar is seen as significantly important which includes data classification, architecture, and collection (Table 9).

Table 9
AHP weights and rank of big data and analytics

Sub-pillars for big data and analytics	**Weights**	**Rank**
Data management	0.415	1
Data mining	0.297	2
Self-organized manufacturing	0.288	3

The results reveal that experts view *access controls* to data resources as the most important factor of *cybersecurity*. Preventing malicious intervention as well as being user-friendly are key factors of access controls. *Communication controls* which include data transmission through networks are followed by *physical controls* setting access standards to tangible assets (Table 10).

Table 10
AHP weights and rank of cybersecurity

Sub-pillars for cybersecurity	**Weights**	**Rank**
Physical controls	0.271	3
Access controls	0.398	1
Communication controls	0.331	2

SaaS, employed for processing data, is considered the first sub-pillar of *the cloud*, followed by *IaaS* which stores data, and *PaaS* which runs applications (Table 11). Processing data gathered in the cloud or transmitted to the cloud is important as it is the main role of a cloud.

Table 11
AHP weights and rank of the cloud

Sub-pillars for the cloud	**Weights**	**Rank**
Infrastructure as a service (IaaS)	0.321	2
Platform as a service (PaaS)	0.309	3
Software as a service (SaaS)	0.370	1

The significance of the *simulation* sub-pillars is revealed as *virtual MRO*, *virtual production*, and *virtual prototyping*, respectively (Table 12). The first expectation from *simulation* is the prediction of proactive maintenance followed by the design and optimization of CPS and process development.

Table 12
AHP weights and rank of simulation

Sub-pillars for simulation	**Weights**	**Rank**
Virtual prototyping	0.256	3
Virtual production	0.328	2
Virtual MRO	0.416	1

When we look at the sub-pillars of *augmented reality*, *operations* is the most significant factor followed by *training*, *service*, and *manufacturing* which have almost equal importance (Table 13). The outcome is not surprising as *operations* describes the immediate interface between the users and *augmented reality* systems that play a crucial role in the success of the results.

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

Table 13
AHP weights and rank of augmented reality

Sub-pillars for augmented reality	Weights	Rank
Training	0.177	2
Design	0.131	5
Manufacturing	0.173	4
Operations	0.227	1
Service	0.176	3
Sales and marketing	0.115	6

Interaction with humans is viewed as more important than *interaction with one another* in assessing *autonomous robots* (Table 14). This finding should be considered when designing the new generation robots compatible with I4.0.

Table 14
AHP weights and rank of autonomous robots

Sub-pillars for autonomous robots	Weights	Rank
Interaction with one another	0.353	2
Interaction with humans	0.647	1

Mass manufacturing employing *additive manufacturing* is a technology unique to the I4.0 environment. The most important factors for building *additive manufacturing* are *VAT polymerization*, *sheet lamination*, *material jetting*, and *powder bed fusion* (Table 15), respectively.

Table 15
AHP weights and rank of additive manufacturing

Sub-pillars for additive manufacturing	Weights	Rank
Binder jetting	0.133	5
Directed energy deposition	0.125	7
Material extrusion	0.128	6
Material jetting	0.152	2
Powder bed fusion	0.145	4
Sheet lamination	0.152	2
VAT polymerization	0.165	1

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

The interdependence between the dimensions, the pillars, and the sub-pillars has been analyzed by the EP as an initial stage of model setting. The paper aims to evaluate the importance of factors in building an I4.0 manufacturing environment, which combines three dimensions, nine pillars, and sub-pillars with distinct technological patterns and maturity levels.

Obviously, the experts each have distinctive perceptions about the pillars, and evaluating their significance ranks entails a thorough disparity. The interdependence across different I4.0 pillars and evaluations of experts displays diversified behavior. The EP put forth that there is no significant interdependence between the dimensions, the criteria, and the sub-criteria. The conclusion of the initial evaluation demonstrated that the AHP method is the most appropriate for the problem, and it was chosen in model and solution.

5. Conclusions

I4.0, also considered the fourth industrial revolution, is a new era of connecting people, equipment, processes, supply chains, and other participants of value creation as a result of the advances in digital technologies. This research proposes a practical and robust MCDM model to support the evaluation of factors in building or assessing the I4.0 system. The study utilized a pairwise survey based on dimensions, pillars, and sub-pillars of I4.0 technologies. The overwhelming majority of literature that taxonomically defines the I4.0 paradigm agrees that I4.0 integrates the nine basic pillars elaborated in this study. The study is the first to focus on the nine pillars of I4.0 in a MCDM context to the best of our knowledge. Hence, the findings of the study are valuable in setting forth the ranks of the pillars and the alignment of projects in transforming to I4.0. The results revealed that *base technologies* are the most significant in configuring I4.0 followed by *smart operations* and *smart technologies*. *Cybersecurity*, *simulation*, and *autonomous robots* are the leading pillars of *base technologies*, *smart operations*, and *smart technologies*, respectively. The sub-pillars are elements such as technologies, equipment, PLCs, sensors, software, or hardware building each pillar. The model also used the evaluation to disentangle the sub-pillars’ comparative significance in the system.

The criteria of I4.0 were assessed by the AHP methodology. The findings reflect the perceptions of I4.0 professionals in evaluating the components and can provide a practical roadmap for the business community as they switch to I4.0. The results of the I4.0 system generated are dependent on the configuration of the pillars. It is complicated to design an optimal I4.0 manufacturing process as each pillar has a varied maturity level and the outcomes of different combinations can be hard to predict. The model we propose is applicable at the corporate level among the I4.0 professionals that make decisions about investments and the study has the potential to trigger new research to elucidate the paradigm of I4.0. Although the AHP model is comprehensive, the results showed the opinions of experts in various industries which can be considered a limitation as each sector has different features necessitating a different I4.0 architecture. Further studies can research the comparative impact of each pillar to support I4.0 technology selection decisions in sectoral clusters to ameliorate this limitation. Most I4.0 professionals are experts on just one specific or a few pillars which made it complicated to find

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

respondents with a complete understanding of all of the pillars. The combining nature of the AHP model helped alleviate this limitation.

A benchmarking study between corporations engaged in I4.0 to compare the systems in operation would be a valuable addition to the literature. As the AHP enables quantitative results from the perceptions of experts, such a study can support the realization of an optimal configuration and highlight areas of improvement. As each pillar has an indispensable impact on the output of I4.0, further studies can focus on the elements of the individual pillars in an MCDM context. Another extension can be employing different applicable methodologies to assess I4.0 technologies.

REFERENCES

Additive Manufacturing Research Group (2019). *The 7 categories of additive manufacturing.* Retrieved from https://www.lboro.ac.uk/research/amrg/about/the7categoriesofadditivemanufacturing/

Akman, E., & Dagdeviren, M. (2018). Discovering what makes a SME website good for international trade. *Technological and Economic Development of Economy*, *24*(3), 1063-1079. Doi: https://doi.org/10.3846/20294913.2016.1266709

Alcácer, V., & Cruz-Machado, V. (2019). Scanning the Industry 4.0: A literature review on technologies for manufacturing systems. *Engineering Science and Technology, an International Journal*, *22*(3), *899-919*. Doi: https://doi.org/10.1016/j.jestch.2019.01.006

Almada-Lobo, F. (2015). The Industry 4.0 revolution and the future of manufacturing execution systems (MES). *Journal of Innovation Management*, *3*(4), 16-21. Doi: https://doi.org/10.24840/2183-0606_003.004_0003

Bahrin, M. A. K., Othman, M. F., Azli, N. N., & Talib, M. F. (2016). Industry 4.0: A review on industrial automation and robotic. *Jurnal Teknologi*, *78*(6-13), 137-143. Doi: https://doi.org/10.11113/jt.v78.9285

Bai, C., Dallasega, P., Orzes, G., & Sarkis, J. (2020). Industry 4.0 technologies assessment: A sustainability perspective. *International Journal of Production Economics*, 229, 107776. Doi: https://doi.org/10.1016/j.ijpe.2020.107776

Blanco-Novoa, O., Fernandez-Carames, T. M., Fraga-Lamas, P., & Vilar-Montesinos, M. A. (2018). A practical evaluation of commercial industrial augmented reality systems in an industry 4.0 shipyard. *IEEE Access*, *6*, 8201-8218. Doi: https://doi.org/10.1109/access.2018.2802699

Bordeleau, F. E., Mosconi, E., & Santa-Eulalia, L. A. (2018, January). Business Intelligence in Industry 4.0: State of the art and research opportunities. In *Proceedings of the 51st Hawaii International Conference on System Sciences*. Doi: https://doi.org/10.24251/HICSS.2018.495

Brettel, M., Friederichsen, N., Keller, M., & Rosenberg, M. (2014). How virtualization, decentralization and network building change the manufacturing landscape: An industry 4.0 perspective. *International Journal of Mechanical, Industrial Science and Engineering*, *8*(1), 37-44. Doi: https://doi.org/10.5281/zenodo.1336426

Calabrese, A., Levialdi Ghiron, N., & Tiburzi, L. (2020). ‘Evolutions’ and ‘revolutions’ in manufacturers’ implementation of industry 4.0: a literature review, a multiple case study, and a conceptual framework. *Production Planning & Control*, 1-15. Doi: https://doi.org/10.1080/09537287.2020.1719715

Chong, L., Ramakrishna, S., & Singh, S. (2018). A review of digital manufacturing-based hybrid additive manufacturing processes. *The International Journal of Advanced Manufacturing Technology*, *95*(5-8), 2281-2300. Doi: https://doi.org/10.1007/s00170-017-1345-3

Contreras-Masse, R., Ochoa-Zezzatti, A., García, V., & Pérez-Dominguez, L. (2020). Implementing a novel use of multicriteria decision analysis to select IIoT platforms for smart manufacturing. *Symmetry*, *12*(3), 368. Doi: https://doi.org/10.3390/sym12030368

Da Silva, V. L., Kovaleski, J. L., & Pagani, R. N. (2019). Technology transfer in the supply chain oriented to industry 4.0: a literature review. *Technology Analysis & Strategic Management*, *31*(5), 546-562. Doi: https://doi.org/10.1080/09537325.2018.1524135

Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018). The expected contribution of Industry 4.0 technologies for industrial performance. *International Journal of Production Economics*, *204*, 383-394. Doi: https://doi.org/10.1016/j.ijpe.2018.08.019

Deloitte Development LLC (Firm). (2020). The fourth industrial revolution: at the intersection of readiness and responsibility.

Dopico, M., Gomez, A., De la Fuente, D., García, N., Rosillo, R., & Puche, J. (2016). A vision of industry 4.0 from an artificial intelligence point of view. In *Proceedings on the International Conference on Artificial Intelligence (ICAI)* (p. 407). The Steering Committee of the World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp).

Erdogan, M., Ozkan, B., Karasan, A., & Kaya, I. (2018). Selecting the best strategy for industry 4.0 applications with a case study. In *Industrial engineering in the industry 4.0 era* (pp. 109-119). Springer, Cham.

Flatt, H., Schriegel, S., Jasperneite, J., Trsek, H., & Adamczyk, H. (2016). Analysis of the cyber-security of industry 4.0 technologies based on RAMI 4.0 and identification of requirements. In *2016 IEEE 21st International Conference on Emerging Technologies and Factory Automation (ETFA)* (pp. 1-4). IEEE. Doi: https://doi.org/10.1109/ETFA.2016.7733634

Fraga-Lamas, P., Fernández-Caramés, T. M., Blanco-Novoa, Ó., & Vilar-Montesinos, M. A. (2018). A review on industrial augmented reality systems for the industry 4.0 shipyard. *IEEE Access*, *6*, 13358-13375. Doi: https://doi.org/10.1109/ACCESS.2018.2808326

Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: implementation patterns in manufacturing companies. *International Journal of Production Economics*, *210*, 15-26. Doi: https://doi.org/10.1016/j.ijpe.2019.01.004

Gauvreau, R. P. (2011). Easy Access to everything-- or how the web can bring it all together. *Iron & Steel Technology*, *8*(1), 63-69.

Ghobakhloo, M. (2020). Determinants of information and digital technology implementation for smart manufacturing. *International Journal of Production Research*, *58*(8), 2384-2405. Doi: https://doi.org/10.1080/00207543.2019.1630775

Gilchrist, A. (2016). *Industry 4.0: the industrial internet of things*. Apress.

Gonzalez, A. G., Alves, M. V., Viana, G. S., Carvalho, L. K., & Basilio, J. C. (2018). Supervisory control-based navigation architecture: a new framework for autonomous robots in industry 4.0 environments. *IEEE Transactions on Industrial Informatics*, *14*(4), 1732-1743. Doi: https://doi.org/10.1109/TII.2017.2788079

He, H., Maple, C., Watson, T., Tiwari, A., Mehnen, J., Jin, Y., & Gabrys, B. (2016). The security challenges in the IoT enabled cyber-physical systems and opportunities for evolutionary computing & other computational intelligence. In *2016 IEEE Congress on Evolutionary Computation (CEC)* (pp. 1015-1021). IEEE. Doi: https://doi.org/10.1109/CEC.2016.7743900

Hermann, M., Pentek, T., & Otto, B. (2016, January). Design principles for industry 4.0 scenarios. In *2016 49th Hawaii International Conference on System Sciences (HICSS)* (pp. 3928-3937). IEEE. Doi: https://doi.org/10.1109/HICSS.2016.488

Hozdic, E. (2015). Smart factory for industry 4.0: A review. *International Journal of Modern Manufacturing Technologies*, *7*(1), 28-35.

International Organization for Standardization (2015). *Additive manufacturing* -- *General principles* -- *Terminology* (ISO/ASTM 52900:2015 (ASTM F2792)). Retrieved from https://www.iso.org/standard/69669.html

Javaid, M., Haleem, A., Vaishya, R., Bahl, S., Suman, R., & Vaish, A. (2020). Industry 4.0 technologies and their applications in fighting COVID-19 pandemic. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*, *14*(4), 419-422. Doi: https://doi.org/10.1016/j.dsx.2020.04.032

Kagermann, H., Wahlster, W., & Helbig, J. (2013). *Recommendations for implementing the strategic initiative INDUSTRIE 4.0: Securing the future of German manufacturing industry; final report of the Industrie 4.0 Working Group*. Forschungsunion.

Kamble, S. S., Gunasekaran, A., & Gawankar, S. A. (2018). Sustainable Industry 4.0 framework: A systematic literature review identifying the current trends and future perspectives. *Process Safety and Environmental Protection*, *117*, 408-425. Doi: https://doi.org/10.1016/j.psep.2018.05.009

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

Karaman, A. S., & Akman, E. (2018). Taking-off corporate social responsibility programs: An AHP application in airline industry. *Journal of Air Transport Management*, *68*, 187-197. Doi: https://doi.org/10.1016/j.jairtraman.2017.06.012

Kaur, H., & Singh, S. P. (2018). Heuristic modeling for sustainable procurement and logistics in a supply chain using big data. *Computers & Operations Research*, *98*, 301-321. Doi: https://doi.org/10.1016/j.cor.2017.05.008

Kobara, K. (2016). Cyber physical security for industrial control systems and IoT. *IEICE TRANSACTIONS on Information and Systems*, *99*(4), 787-795. Doi: https://doi.org/10.1587/transinf.2015ICI0001

Lasi, H., Fettke, P., Kemper, H. G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. *Business & Information Systems Engineering*, *6*(4), 239-242. Doi: https://doi.org/10.1007/s11576-014-0424-4

Lee, J., Bagheri, B., & Kao, H. A. (2014a, July). Recent advances and trends of cyber-physical systems and big data analytics in industrial informatics. In *Proceeding of International Conference on Industrial Informatics (INDIN)* (pp. 1-6).

Lee, J., Kao, H. A., & Yang, S. (2014b). Service innovation and smart analytics for industry 4.0 and big data environment. *Procedia CIRP*, *16*, 3-8. Doi: https://doi.org/10.1016/j.procir.2014.02.001

Liao, Y., Deschamps, F., Loures, E. D. F. R., & Ramos, L. F. P. (2017). Past, present and future of Industry 4.0-a systematic literature review and research agenda proposal. *International Journal of Production Research*, *55*(12), 3609-3629. Doi: https://doi.org/10.1080/00207543.2017.1308576

Lu, Y. (2017). Industry 4.0: A survey on technologies, applications and open research issues. *Journal of Industrial Information Integration*, *6*, 1-10. Doi: https://doi.org/10.1016/j.jii.2017.04.005

Luthra, S., & Mangla, S. K. (2018). Evaluating challenges to Industry 4.0 initiatives for supply chain sustainability in emerging economies. *Process Safety and Environmental Protection*, *117*, 168-179. Doi: https://doi.org/10.1016/j.psep.2018.04.018

Manfredi, D., Calignano, F., Krishnan, M., Canali, R., Ambrosio, E. P., Biamino, S., ... & Fino, P. (2014). Additive manufacturing of Al alloys and aluminium matrix composites (AMCs). *Light Metal Alloys Applications*, *11*, 3-34. Doi: https://doi.org/10.5772/58534

Marr, B. (2015). Big Data: 20 mind-boggling facts everyone must read. *Forbes Magazine*.

Marr, B. (2016). What everyone must know about industry 4.0. *Forbes Tech*.

Mercer, D., (2019). *Global Connected and IoT Device Forecast Update Report*, Strategy Analytics.

Mohammad, E., AlBarakah, L., Kudair, S., & Karaman, A. S. (2021, March). Evaluating the Industry 4.0 readiness of manufacturing companies: A case study in Kuwait. In *11th International Conference on Industrial Engineering and Operations Management, IEOM 2021, Singapore* (pp. 6625-6636). IEOM Society.

Moreno, A., Velez, G., Ardanza, A., Barandiaran, I., de Infante, Á. R., & Chopitea, R. (2017). Virtualisation process of a sheet metal punching machine within the Industry 4.0 vision. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, *11*(2), 365-373. Doi:10.1007/s12008-016-0319-2.

Motyl, B., Baronio, G., Uberti, S., Speranza, D., & Filippi, S. (2017). How will change the future engineers' skills in the Industry 4.0 framework? A questionnaire survey. *Procedia Manufacturing*, *11*, 1501-1509. Doi: https://doi.org/10.1016/j.promfg.2017.07.282

Mourtzis, D., Doukas, M., & Bernidaki, D. (2014). Simulation in manufacturing: Review and challenges. *Procedia CIRP*, *25*, 213-229. Doi: https://doi.org/10.1016/j.procir.2014.10.032

Mourtzis, D., Zogopoulos, V., & Vlachou, E. (2017). Augmented reality application to support remote maintenance as a service in the robotics industry. *Procedia CIRP*, *63*, 46-51. Doi: https://doi.org/10.1016/j.procir.2017.03.154

Müller, J. M., Buliga, O., & Voigt, K. I. (2018). Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0. *Technological Forecasting and Social Change*, *132*, 2-17. Doi: https://doi.org/10.1016/j.techfore.2017.12.019

Negahban, A., & Smith, J. S. (2014). Simulation for manufacturing system design and operation: Literature review and analysis. *Journal of Manufacturing Systems*, *33*(2), 241-261. Doi: https://doi.org/10.1016/j.jmsy.2013.12.007

Negri, E., Fumagalli, L., & Macchi, M. (2017). A review of the roles of digital twin in cps-based production systems. *Procedia Manufacturing*, *11*, 939-948. Doi: https://doi.org/10.1016/j.promfg.2017.07.198

Öberseder, M., Schlegelmilch, B. B. and Murphy, P. E. (2013). CSR practices and consumer perceptions. *Journal of Business Research*, *66*(10), 1839-1851. Doi: https://doi.org/10.1016/j.jbusres.2013.02.005

Oztemel, E., & Gursev, S. (2020). Literature review of Industry 4.0 and related technologies. *Journal of Intelligent Manufacturing*, *31*(1), 127-182. Doi: https://doi.org/10.1007/s10845-018-1433-8

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

Posada, J., Toro, C., Barandiaran, I., Oyarzun, D., Stricker, D., de Amicis, R., ... & Vallarino, I. (2015). Visual computing as a key enabling technology for industrie 4.0 and industrial internet. *IEEE Computer Graphics and Applications*, *35*(2), 26-40. Doi: https://doi.org/10.1109/MCG.2015.45

Prause, G. (2015). Sustainable business models and structures for Industry 4.0. *Journal of Security & Sustainability Issues*, *5*(2), 159-169. Doi: https://doi.org/10.9770/jssi.2015.5.2(3)

Press, G. (2013). A very short history of big data. *Forbes Tech Magazine*.

Qi, Q., & Tao, F. (2018). Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. *IEEE Access*, *6*, 3585-3593. Doi: https://doi.org/0.1109/ACCESS.2018.2793265

Rodič, B. (2017). Industry 4.0 and the new simulation modelling paradigm. *Organizacija*, *50*(3), 193-207. Doi: https://doi.org/10.1515/orga-2017-0017

Rosa, P., Sassanelli, C., Urbinati, A., Chiaroni, D., & Terzi, S. (2020). Assessing relations between Circular Economy and Industry 4.0: a systematic literature review. *International Journal of Production Research*, *58*(6), 1662-1687. Doi: https://doi.org/10.1080/00207543.2019.1680896

Rüßmann, M., Lorenz, M., Gerbert, P., Waldner, M., Justus, J., Engel, P., & Harnisch, M. (2015). Industry 4.0: The future of productivity and growth in manufacturing industries. *Boston Consulting Group, 9*(1), 54-89.

Saaty, T. (1980). *The analytic hierarchy process: planning, priority setting, resource allocation*. Pittsburgh PA: University of Pittsburgh.

Sadeghi, A. R., Wachsmann, C., & Waidner, M. (2015, June). Security and privacy challenges in industrial internet of things. In *2015 52nd ACM/EDAC/IEEE Design Automation Conference (DAC)* (pp. 1-6). IEEE. Doi: https://doi.org/10.1145/2744769.2747942

Schleich, B., Anwer, N., Mathieu, L., & Wartzack, S. (2017). Shaping the digital twin for design and production engineering. *CIRP Annals*, *66*(1), 141-144. Doi: https://doi.org/10.1016/j.cirp.2017.04.040

Singh, J., Garg, D., & Luthra, S. (2018). An analysis of critical success factors for Industry 4.0: An application of Analytical Hierarchy Process. *Industrial Engineering Journal*, *11*(9), 1-15.

Sony, M., & Naik, S. (2020). Critical factors for the successful implementation of Industry 4.0: a review and future research direction. *Production Planning & Control*, *31*(10), 799-815. Doi: https://doi.org/10.1080/09537287.2019.1691278

Stock, T., & Seliger, G. (2016). Opportunities of sustainable manufacturing in industry 4.0. *Procedia CIRP*, *40*, 536-541. Doi: https://doi.org/10.1016/j.procir.2016.01.129

Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. *Journal of Manufacturing Systems*, *48*, 157-169. Doi: https://doi.org/10.1016/j.jmsy.2018.01.006

Thames, L., & Schaefer, D. (2016). Software-defined cloud manufacturing for industry 4.0. *Procedia CIRP*, *52*, 12-17. Doi: https://doi.org/10.1016/j.procir.2016.07.041

Tofail, S. A., Koumoulos, E. P., Bandyopadhyay, A., Bose, S., O'Donoghue, L., & Charitidis, C. (2018). Additive manufacturing: Scientific and technological challenges, market uptake and opportunities. *Materials Today*, *21*(1), 22-37. Doi: https://doi.org/10.1016/j.mattod.2017.07.001

Uhlemann, T. H. J., Lehmann, C., & Steinhilper, R. (2017). The digital twin: Realizing the cyber-physical production system for industry 4.0. *Procedia CIRP*, *61*, 335-340. Doi: https://doi.org/10.1016/j.procir.2016.11.152

Vaidya, S., Ambad, P., & Bhosle, S. (2018). Industry 4.0–a glimpse. *Procedia Manufacturing*, *20*, 233-238. Doi: https://doi.org/10.1016/j.promfg.2018.02.034

Vogel-Heuser, B., & Hess, D. (2016). Guest editorial industry 4.0–prerequisites and visions. *IEEE Transactions on Automation Science and Engineering*, *13*(2), 411-413. Doi: https://doi.org/10.1109/tase.2016.2523639

Vrochidis, S., Papadopoulos, S., Moumtzidou, A., Sidiropoulos, P., Pianta, E., & Kompatsiaris, I. (2010). Towards content-based patent image retrieval: A framework perspective. *World Patent Information*, *32*(2), 94-106. Doi: https://doi.org/10.1016/j.wpi.2009.05.010

Waidner, M., & Kasper, M. (2016, March). Security in industrie 4.0-challenges and solutions for the fourth industrial revolution. In *2016 Design, Automation & Test in Europe Conference & Exhibition (DATE)* (pp. 1303-1308). IEEE.

Wan, J., Tang, S., Shu, Z., Li, D., Wang, S., Imran, M., & Vasilakos, A. V. (2016). Software-defined industrial internet of things in the context of industry 4.0. *IEEE Sensors Journal*, *16*(20), 7373-7380. Doi: https://doi.org/10.1109/JSEN.2016.2565621

Wang, S., Wan, J., Zhang, D., Li, D., & Zhang, C. (2016). Towards smart factory for industry 4.0: a self-organized multi-agent system with big data-based feedback and coordination. *Computer Networks*, *101*, 158-168. Doi: https://doi.org/10.1016/j.comnet.2015.12.017

Wang, L., & Wang, G. (2016). Big data in cyber-physical systems, digital manufacturing and industry 4.0. *International Journal of Engineering and Manufacturing (IJEM)*, *6*(4), 1-8. Doi: https://doi.org/10.5815/ijem.2016.04.01

Weyer, S., Meyer, T., Ohmer, M., Gorecky, D., & Zühlke, D. (2016). Future modeling and simulation of CPS-based factories: an example from the automotive industry. *IFAC-PapersOnLine*, *49*(31), 97-102. Doi: https://doi.org/10.1016/j.ifacol.2016.12.168

Weyer, S., Schmitt, M., Ohmer, M., & Gorecky, D. (2015). Towards Industry 4.0-Standardization as the crucial challenge for highly modular, multi-vendor production systems. *Ifac-Papersonline*, *48*(3), 579-584. Doi: https://doi.org/10.1016/j.ifacol.2015.06.143

Wollschlaeger, M., Sauter, T., & Jasperneite, J. (2017). The future of industrial communication: Automation networks in the era of the internet of things and industry 4.0. *IEEE Industrial Electronics Magazine*, *11*(1), 17-27. Doi: https://doi.org/10.1109/mie.2017.2649104

Xu, J., Huang, E., Hsieh, L., Lee, L. H., Jia, Q. S., & Chen, C. H. (2016). Simulation optimization in the era of Industrial 4.0 and the Industrial Internet. *Journal of Simulation*, *10*(4), 310-320. Doi: https://doi.org/10.1057/s41273-016-0037-6

Zawadzki, P., & Żywicki, K. (2016). Smart product design and production control for effective mass customization in the Industry 4.0 concept. *Management and Production Engineering Review*, *7*(3), 105-112. Doi: https://doi.org/10.1515/mper-2016-0030

Zhong, R. Y., Xu, X., Klotz, E., & Newman, S. T. (2017). Intelligent manufacturing in the context of industry 4.0: a review. *Engineering*, *3*(5), 616-630. Doi: https://doi.org/10.1016/J.ENG.2017.05.015

Zhou, K., Liu, T., & Zhou, L. (2015, August). Industry 4.0: Towards future industrial opportunities and challenges. In *2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)* (pp. 2147-2152). IEEE. Doi: https://doi.org/10.1109/FSKD.2015.7382284

APPENDIX

PILLARS IN THE MAKING, INDUSTRIE 4.0 ON THE HORIZON

Instructions:

Please compare the below dimension / pillar / sub-pillar couplet based on their relative importance to each other.

Only one box is going to be checked in the comparisons.

If the item on the left is more important than the item on the right, please use the scale on the left of "1" and indicate its relative importance.

If the item on the right is more important than the item on the left, please use the scale on the right of "1" and indicate its relative importance.

If the items have equal importance, than check the box for "1".

Intensity of Importance	Definition
1	Equal Importance
3	Moderate Importance
5	Strong Importance
7	Very Strong Importance
9	Absolute Importance
2, 4, 6, 8 can be used to express intermediate values.	

COMPARING THE DIMENSIONS

	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
Base technologies																		Smart operations
Base technologies																		Smart technologies
Smart operations																		Smart technologies

COMPARING THE PILLARS

Base technologies	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
The industrial internet of things (IIoT)																		Horizontal and vertical system integration
The industrial internet of things (IIoT)																		Big data and analytics
The industrial internet of things (IIoT)																		Cybersecurity
The industrial internet of things (IIoT)																		The cloud
Horizontal and vertical system integration																		Big data and analytics
Horizontal and vertical system integration																		Cybersecurity
Horizontal and vertical system integration																		The cloud
Big data and analytics																		Cybersecurity
Big data and analytics																		The cloud
Cybersecurity																		The cloud

COMPARING THE PILLARS

Smart operations	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
Simulation																		Augmented reality

COMPARING THE PILLARS

Smart technologies	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
Autonomous robots																		Additive manufacturing

COMPARING THE SUB-PILLARS

Base technologies

The industrial internet of things (IIoT)	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
Physical layer																		Network layer
Physical layer																		Service layer
Physical layer																		Interface layer
Network layer																		Service layer
Network layer																		Interface layer
Service layer																		Interface layer
Horizontal and vertical system integration	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
Horizontal integration																		Vertical integration
Horizontal integration																		End-to-end integration
Vertical integration																		End-to-end integration
Big data and analytics	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
Data management																		Data mining
Data management																		Self-organized manufacturing
Data mining																		Self-organized manufacturing
Cybersecurity	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
Physical controls																		Access controls
Physical controls																		Communication controls
Access controls																		Communication controls
The cloud	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
Infrastructure as a service (IaaS)																		Platform as a service (PaaS)
Infrastructure as a service (IaaS)																		Software as a service (SaaS)
Platform as a service (PaaS)																		Software as a service (SaaS)

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839

COMPARING THE SUB-PILLARS																		
Smart operations																		
Simulation	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
Virtual prototyping																		Virtual production
Virtual prototyping																		Virtual maintenance, repair and operations (MRO)
Virtual production																		Virtual maintenance, repair and operations (MRO)
Augmented reality	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
Training																		Design
Training																		Manufacturing
Training																		Operations
Training																		Service
Training																		Sales and marketing
Design																		Manufacturing
Design																		Operations
Design																		Service
Design																		Sales and marketing
Manufacturing																		Operations
Manufacturing																		Service
Manufacturing																		Sales and marketing
Operations																		Service
Operations																		Sales and marketing
Service																		Sales and marketing

COMPARING THE SUB-PILLARS																		
Smart technologies																		
Autonomous robots	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
Interaction with one another																		Interaction with humans
Additive manufacturing	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
Binder jetting																		Directed energy deposition
Binder jetting																		Material extrusion
Binder jetting																		Material jetting
Binder jetting																		Powder bed fusion
Binder jetting																		Sheet lamination
Binder jetting																		VAT polymerisation
Directed energy deposition																		Material extrusion
Directed energy deposition																		Material jetting
Directed energy deposition																		Powder bed fusion
Directed energy deposition																		Sheet lamination
Directed energy deposition																		VAT polymerisation
Material extrusion																		Material jetting
Material extrusion																		Powder bed fusion
Material extrusion																		Sheet lamination
Material extrusion																		VAT polymerisation
Material jetting																		Powder bed fusion
Material jetting																		Sheet lamination
Material jetting																		VAT polymerisation
Powder bed fusion																		Sheet lamination
Powder bed fusion																		VAT polymerisation
Sheet lamination																		VAT polymerisation

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v13i2.839