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Article

Role of Computer-Aided Systems in Production Flexibility: A study of the application of industry 4.0 technological concepts in manufacturing industries

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Abstract: Sustainability is the core concern of every business; The exploration of avenues to maintain sustainability while staying competitive with high level of productivity remains a vital endeavor. Production flexibility is a key area that can enhance the sustainability of manufacturing industries; can ensure product availability, scalability, agility/fault tolerance as well as disaster recovery potentials. Technological advancements have provided avenues where companies can enhance virtually all aspects of their operations for efficiency, effectiveness, and productivity. This paper uses both quantitative and qualitative research approach to identify the capability requirements for smart and effective production management and subsequent analysis is done using Multi-Criteria Decision-Making methodology to identify and rank various industry 4.0 technologies and concepts that can provide these smart capabilities in manufacturing industries to aid the businesses to achieve sustainability with production flexibility. The paper identifies over 12 smart capabilities and 9 Industry 4.0 Technologies which are applicable to production management. It also compares results from the analytics of historical I4.0 implementation as discussed in literatures with the current state as deduced from survey feedbacks from various manufacturing industries.

Keywords: Industry 4.0; HMLV; LMHV; Production scheduling; Digital Manufacturing; Computer aided production management (CAPM); Smart Manufacturing; MCDM

1. Introduction

Dynamic and uncertain production environment is a major factor in the industries today and present market demands require that manufacturing systems develop their activities under such conditions. The influence of economic, social, political, and environmental factors can be very unpredictable, and these are paramount when considering any production environment because these factors can contribute to the sustainability/success or failure of industries. Owing to the above-mentioned facts, it is necessary to incorporate the concept of flexibility in manufacturing. This ability to give quick and efficient answers to the uncertainties in local, national, and international market is vital and production flexibility is a strategic topic in such decision making [1, 2].

The advent of the Fourth industrial revolution has introduced many technologies that give businesses the ability to incorporate very high levels of flexibility in their operation. Its impact can be seen in various aspects of business activities ranging from human resources, finance, operations, marketing etc. Virtually all aspects of any industry can be positively impacted by the technologies of industry 4.0 [1, 3-5]. In this research, we shall identify and outline the various industry 4.0 Technologies and the capability requirements for production planning that will contribute to production flexibility.

Another vital aspect for production flexibility and business sustainability is the effective management of resources. This is where production scheduling plays a key role for the establishment of timing and the use of resources of the organization which include equipment, facilities, and human activities. Every manufacturing industry must develop schedule for workers, equipment, purchases, maintenance etc.; effective scheduling results to cost savings, increase in productivity among other benefits [5]. We shall discuss various scheduling approaches and methodologies that can be implemented in manufacturing.

The analysis and investigation in this research will focus on the use of decision-making systems for the identification technology implementations for production and combination of these together with quality function deployment approach for production scheduling to ensure flexibility in manufacturing and business sustainability.

2. Materials

2.1. Industry 4.0 - Requirements for Digitalized Manufacturing

In the past century there has been rapid advancements in technology, applications, and industry and numerous concepts have emerged in manufacturing. Since the first industrial revolution, which introduced mechanization, subsequent industrial revolutions have resulted in sweeping changes in manufacturing. The second industrial revolution saw the rationalization and division of labor in manufacturing industries while the third industrial revolution brought electricity and advanced electronics which increased productivity as well as calculation and data/information storage capacities. The notion of the fourth industrial revolution was introduced at the end of the 20th century and it was centered around promoting the idea of digitization together with autonomy and self-control where products tend to control their own manufacturing process. [6-8]

The fourth industrial revolution or Industry 4.0 (I4.0) can be summarized as the use of technology in a way that businesses and engineering processes are integrated in such a way that makes manufacturing flexible, resource efficient and sustainable. Businesses are striving to implement concepts of Industry 4.0 to transform business processes however, the maturity level of various companies vary, and the impact can be seen in different aspects of their operations. Some of the characteristics of mature companies include having clear digital strategy, building skills, and capabilities to implement strategy, flexibility/ability to adapt, use of KPIs for machine learning, decentralized decision making, and digital fluent leadership. Two main approaches which serves as guidance to implementing I4.0 concepts are the "holistic approach", which tries to use all avenues to access and utilize elements of I4.0 to drive success factors. In this approach maturity self-assessments are conducted to provide strategic guidance and related tools for implementation. This approach usually lacks transparency at is not scientifically grounded. The other approach is the "Specific approach" which employs data analytics and maintenance aspect, knowledge intensive business processes, digital information systems, big data usage, logistics and supply chain etc. to determine I4.0 maturing level and develop roadmap for implementation. [6, 9-12]

I4.0 provides businesses with increased visibility. Production managers can access real time supply and demand related data making it easier to optimize operations, reduce resources and lead times [10]. The literature on Industry 4.0 is widespread and many scholars have written on various aspect of it. The purpose of this literature is not to examine the holistic aspects of I4.0. However, the main objective is to investigate the requirements of industry 4.0 as it relates to production planning and control, supply chain and production strategies.

2.1.1 Industry 4.0 Concepts and Technologies

Industrial revisions require long term developments that cover four key areas: Factory, Business, Products and Customers. The future factory will be one where all manufacturing resources ranging from sensors, robots, conveyor machines etc. are connected and exchange information as well as become intelligent enough to predict and maintain machines, control production process and in general manage the factory system. The business aspect involves a communication network between various companies, factories, suppliers, logistics etc. aimed at optimizing configurations in real time to maximize profit. Products will contain sensors, processors and components which carry functional

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guidance for the customers and in turn transmits usage feedback to the manufacturing system for use in product improvement. The area of customers mean that they will have significant influence in the manufacturing process, product functions will be determined and customized by customers [4, 5, 7, 8, 13-16]. Industry 4.0 concepts are geared towards the achievement of the various areas of industrial revision. We shall explore the overview of various industry 4.0 concepts/requirements, application of these concepts, value creations and how fit into the production lifecycle.

Cyber-Physical Systems (CPS): There has been a fundamental change in the way IT services are developed, deployed, and maintained. This is due to the emergence of cloud computing. Cyber-physical systems and cloud computing has made industries become more efficient, autonomous, and customized [17]. CPS is the integration of the physical with the virtual world. It is aimed at integrating embedded systems, control, computing, communication, and network devices. It also consists of the security procedures like hardware encryption and network security for data transit. CPS closely connect systems thereby blurring the boundaries between real and virtual factories [18]. The main aim of cyber-physical management systems is to give exact directions which the system must follow for fulfilling the operation to the expected level. This is also referred to as smart manufacturing and the heterogeneity of the system is made up of entities ranging from small sensors to large scale processing elements. When CPS is implemented in production planning and control, it can be termed Cyber-physical Production System (CPPS). CPPS retrofitting process is used to transform/update industrial equipment for industry 4.0 integration [17-19]. In summary, the key capabilities that CPS introduces are real-time data processing and information feedback, computational capabilities, and decision-making capability.

Cloud Computing: This I4.0 concept usually works alongside CPS. It is sometimes referred to as an aspect of CPS [19]. The National Institute of Standards and Technology outlines three service model related to cloud computing: these include Software as a Service (SaaS); Platform as a Service (PaaS) and Infrastructure as a Service (IaaS). IaaS is the most basic cloud computing service. It is an instant computing infrastructure, provisioned and managed over the internet. Common uses of IaaS are product Test and Development environments, storage, backup and recovery, workload migration etc. PaaS provides development environment for users to manage cloud-based applications without bothering about the building and maintenance of the infrastructure. Common usage scenarios of PaaS are development framework and Analytics or business intelligence. SaaS is software that is centrally hosted and managed for the end customer. It allows users to use apps over the internet. Examples of SaaS usage is Skype, Microsoft 365, Microsoft Dynamic CRM, Oracle CRM, ERP, SCM, CAD, FEA, etc. In this form of service, the end user is barely responsible for the provision, management, and maintenance of the application software which in turn saves costs [4, 11, 17, 19, 20]. Summary of key capabilities of Cloud computing are Location and sourcing independence, Ubiquitous access, and Integrated Business Environment and operations.

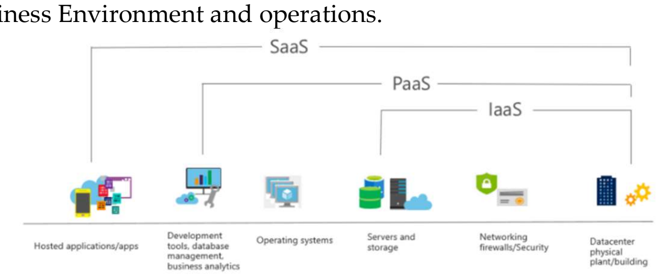

Figure 1: Cloud services [20]

Internet of Things (IoT): There are several definitions of IoT most of which are from authors perspective. For this study, we will review IoT in the context of production manufacturing. IoT brings the convergence of connected products and sensors to introduce new capabilities. It refers to the robust communication between digital and physical world. Sensors, Actuators, RFID, and RTLS are used to achieve these forms of communication. IoT influence is being rampant in various industries ranging from automotive, aerospace, supply chain, construction, and manufacturing sector etc. [21-23]. IoT is leading the foundation of Industry 4.0 in several sectors ranging from smart transport solutions, smart health, smart cities, and smart factories etc. [23]. The main role of IoT is devices is the dual provision of accurate information in real-time and this possibility opens new analytical possibilities and fast result dissemination, thereby assisting decision-making process. Technologies like RFID and RTLS provide capabilities such as identification, location, and sensing. While Sensor and Actuators provide Real-time tracking, Continuous documentation and data collection, process synchronization and system availability. [4, 7, 8, 21-23]

Big Data and Analytics/ Artificial Intelligence (BDA/AI): Operations managers use advanced analytics for the exploration of historical data, pattern identification and relationships to enable them optimize factors that have greatest effects in their processes. The manufacturing industry is perceived to be to greatest generator of data when compared with other sectors therefore there is very high value to be captured from big data analytics [4, 24, 25]. IoT and AI are the major technologies that drive I4.0; they usually operate together as the data from IoT serves as input for AI [26]. Industrial application of AI focuses on the development, validation and deployment of various machine learning algorithms and analytics for industrial applications with sustainable performance [24]. Data-based decision making has evolved from decision support to executive support with focus on data exploration for top management decision making. Over the last decade, many software tools have been developed for the analytics of multidimensional data. Business Intelligence software like Tableau, Power BI, Oracle BI, Sisense, SAP business objects etc. have become common place in manufacturing industries to provide data analytics, real time reporting, embedded analytics, and natural language processing services. The summary of the capabilities of DBA/AI includes Analysis of large amount of Data within a short period of time, Retention of data knowledge, and learning from data [4, 6, 7, 24-27].

Additive Manufacturing (AM): This is a "range of technologies that translate virtual model data into physical models or prototypes through a process of depositing successive layers of material of finite thickness" [4]. It provides fast and less costly means to create prototypes for real world simulation. AM is usually is sometimes referred to as 3D printing which consists of set of process technologies that can directly produce parts through incremental addition of material layers of joining materials [28].

Additive manufacturing offers tremendous opportunities for existing production processes. The fast pace of advancements in this area is making it easier and less expensive to manufacture products and product parts that would otherwise be very complicated and expensive to produce. The material science field is a very vital field which the AM depends on. Researchers in this field are constantly developing new materials for 3D printing applications. AM technologies can have extreme impact on production planning and control, and it has the potential of giving industries high degree of production flexibility in areas of product redesign and modification. In this I4.0 age, several materials have been developed or are under developments that are suitable for application in AM [4, 28-30]. There materials are grouped into 4 as shown in Figure 2 below:

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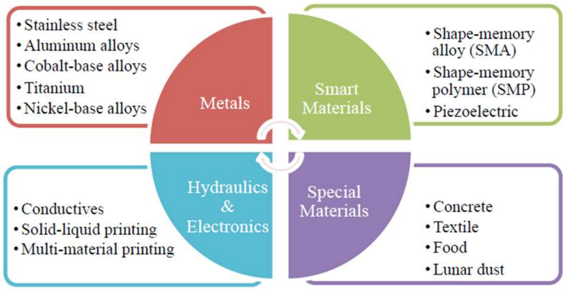

Figure 2: General Overview of current research materials for AM [29]

To standardize the constantly evolving technology of Additive Manufacturing, the International Standards Organization (ISO) together with the American Society for Testing and Materials (ASTM) classified the scope of additive manufacturing into 7 types [31]:

I. Material Extrusion: In this type of AM, material in a filament form is drawn through a nozzle, heated, and then extruded and deposited in layers onto a build platform. It offers quick prototyping of simple parts and commonly used for printing household items, toys, games, and similar products.

II. VAT photopolymerization: This uses a vat of liquid photosensitive polymer resin which hardens on exposure to UV light to build objects layer-by-layer.

III. Powder Bed Fusion: This type of AM fuses powdered material to additively create 3D objects. IT uses a laser electron beam to sinter, melt and fuse powder together while it traces the cross section of the object to be created. This process is repeated layer by layer until object is built.

IV. Material Jetting: This works in similar way as the inkjet printer by depositing a photosensitive polymer liquid which harden on exposure to UV light thereby building the part layer by layer. It is typically used for building parts that require high dimensional accuracy and smooth surface finish.

V. Binder Jetting: It is like material jetting but uses two material instead of one. The two materials are a powder base material and a binder material. The binder material acts as a binding agent for individual layers of the powder material.

VI. Sheet Lamination: this process includes two types of manufacturing techniques, Ultrasonic Additive Manufacturing (UAM) where sheets or ribbons of metal are bound together using ultrasonic welding after which the parts do not require any additional step of machining or removal of material. The other type is the Laminated Object Manufacturing (LOM) which uses sheets of paper as base material and adhesive in place of welding. Objects manufactured with this process are not fit for structural us and can only be used for aesthetic purpose.

VII. Direct Energy Deposition (DED): This is typically used for 3D printing of metal and alloys. In DED, a nozzle holds the material in a wire form which is known as a feed and moves across multiple axis and an electron beam projector which melts the feed as it moves across while tracing the object geometry. DED method is also called as Laser engineered net shaping, 3D laser cladding, directed light fabrication or direct metal deposition

Various forms and shapes of products can be easily manufactured by the above additive manufacturing type simply by using data from 3D computer models [28, 31, 32]. The key capabilities that AM introduces are new geometry possibilities, shorter time-to-market, unique material.

Simulation: Simulation involves modelling of processes or systems, so that the model mimics responses of the actual system to events that take place over time. Supports experimentation and validation of different scenarios and configurations for existing and new manufacturing resources and systems, contributing to an improved design and performance assessment [33]. Modeling and simulation have become vital parts of industrial engineering, operations, and supply chain management. It enables the management of

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complex systems. "Modeling and simulation denote a set of methods and technological tools that allows the experimentation and validation of products, processes, systems design and to predict system performance. It also supports decision making, education and training, aiding to reduce costs and development cycles" [34]. Some simulation approaches include Agent-Based Modeling and Simulation (ABMS), Discrete Event Simulation (DES), System Dynamics (SD), Virtual Reality (VR), Augmented Reality (AR), Petri Nets simulation (PN), Hybrid Simulation (HS)-which involves the combination of two or more simulation methods, Digital Twins (DT), Virtual Commissioning (VC) etc. [7, 33, 34].

I4.0 capabilities which Simulation offers include decision making support, evaluation of autonomous planning rules and digital twin model.

Cybersecurity: The advent of I4.0 has seen very high degree of digitalization of manufacturing processes, systems, and industries. In some instances, the entire value chain of manufacturing industries has extremely high degree of digital interconnectivity and this possess the absolute need for security of the system.

CISCO defined cybersecurity as the practice of protecting systems, networks, and programs from digital attacks. The implementation of effective cybersecurity is a very challenging and dynamic undertaking. The approach of implementing multiple layers of protection across networks, computer, programs, or data constitutes a successful cybersecurity [35]. The goal of cybersecurity is three-fold; Confidentiality which involves prevention of unauthorized disclosure of sensitive data and information. Integrity which constitutes maintaining the consistency, accuracy, and trustworthiness of the data. Availability involves keeping data and resources available for authorized use [4].

Mobile Technologies: This is one of the driving forces behind Industry 4.0, creating "smart factories" and streamlining manufacturing operations with mobility [3]. It consists of the wireless integration of communication technology based on wireless devices [36]. Mobile technology in manufacturing brings vast palpable improvement in industries with enhancements across all divisions from the shop floor to warehouse to management. The concept of I4.0 requires manufacturing operations to be closely connected, wherein communication and cooperation happens among machines and with people in real time via wireless web. We can view the benefits of mobile technology in two aspects: The benefits in manufacturing and the benefits in operations. The main benefits of mobility in manufacturing include, but not limited to; portability, real-time problems/real-time solutions, Relatability to increase worker productivity (Task-on-the-go) and precision monitoring. The operational benefits include overall productivity increase, cost reduction, increased efficiency, fast access to critical information, Connectivity, and interaction from anywhere at any time of anything, collaboration between people at all levels, improved return on investment, increased customer reach and Sales, competitive edge etc. [3, 7, 36].

Adaptive Robotics: The growing popularity of I4.0 has led to dramatic developments in robotic technology. They are those categories of devices that can be programmed to perform activities with little or no human intervention. There are numerous predictions on the direction of robotics, and they all tend to make same point which is that the next generation of robotics and its associated technologies will play more pronounced roles to meet the need of collaborative and intelligent manufacturing. Autonomous robots and cobots are very important technology for plant automation and commissioning. With robotics in manufacturing the numerous capabilities are introduced, control and autonomy, communication efficiency, high computation, near certainty in output, etc. [24, 36, 37].

These Industry-4.0 concepts and technologies discussed are relatively novel and they seek to overcome contemporary challenges such as global competition, volatile markets and demand, increased customization through communication, information, and intelligence, and decreasing innovation and product life cycles [38].

2.2. Production Strategies

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The ever-growing importance of production planning is due to the dynamism, complexity, and the globalization of economies. Production planning is a tool which enables firms to react as flexibly as is required by the market. Speedy response to customer is vital for customer satisfaction in a diverse and ever-changing market [18]. Production strategies aims to determine best possible ways and justifications to determine what, how much, when to produce, buy, and deliver so that company can match manufacturing performances with customer demands. It is a value adding process of the manufacturing activity [36].

In this section, we will discuss two manufacturing types: High-mix Low-volume (HMLV) and Low-mix High-Volume (LMHV) Manufacturing strategies. For this study, more emphasis will be laid on HMLV and the various factors, requirements and capabilities that promote flexible and sustainable manufacturing.

Low-Mix High-Volume Manufacturing

This type of manufacturing is sometimes referred to as mass production. It involves the fabrication of large quantity of products that have little or no variation. Manufacturers employ a variety of techniques and technologies to achieve high levels of output ranging from automation of certain production tasks, assembly lines, etc. Two main advantage of this form of manufacturing is the high level of output within a short period of time, ease of automation and digitalization, does not require highly skilled workers and reduced overall cost of production per unit. Some of the disadvantage of this type of manufacturing is that there is usually high upfront cost, inability to meet specific desires of customers and low production flexibility [39].

High-Mix Low Volume Manufacturing

High-mix Low-Volume (HMLV) production is a type of production that allows for a high variety of products to be produced in relatively small amount [18]. It is sometimes referred to as "Mass Customization" as it focuses on providing individualized products [40]. Production management is a very vital field that requires adequate attention in every industry. It contains the tasks of design, planning, monitoring and control of the productive system and business resources such as people, processes, machine, material, and information [7]. In HMLV manufacturing, production management is a daunting task and every aspect must be vigorously monitored and optimized for a company to remain competitive [2, 7, 8, 30, 31, 40, 41].

Several methods have been deployed to support production process; an example being the Total Productive Maintenance whose goal is to increase the effectiveness of production equipment based on the idea that six types of losses (Equipment failure, setup and adjustment times, idling and minor stoppages, reduce equipment speed, defects and reduced yield) can be identified and reduced. In this approach, Overall Equipment Effectiveness is used as performance indicator; However, unlike in mass production, application of this in HMLV manufacturing means such analysis is only done by considering the individual product parameters and mathematically combine this to derive OEE performance factor value for entire production.

There are many literatures which discussed various HMLV production planning techniques and models aimed at the optimization of manufacturing. However, the scope of this study is not to discuss the specific techniques but rather to outline the general capabilities required to achieve these strategies to identify the industry 4.0 technologies that will assist, promote, or enhance the implementation of such production strategies.

One of the major capability requirements for HMLV production systems is **real-time** decision-making support system for various aspects like production scheduling [18]. The ability to manage resources, logistics flow, products, and support manufacturing decisions in real time coupled with other complexities involved in HMLV manufacturing begs the need for several aspects of production planning and control to be smart and technologically optimized. An extension of this real time capability requirement is **visibility and**

traceability which has to do with the ability to trace, visualize, and make decisions regarding resources information and products. **Adaptability and dynamism** as well as the **scalability and reconfiguration** are also vital capability requirements in PPC activities of HMLV manufacturing environments. These determine the degree of dynamism on product, process, or demand and ability of PPC to change its configurations flexibly and easily. The ability of manufacturing industries to synchronize the planning and control activities with the physical manufacturing environment in real time. (Routes, flows, data, operations, systems etc.) is paramount for production flexibility and sustainability. This capability requirement can be referred to as **synchronization**. Planning and control need integration into new and legacy systems and reach full interoperability between system layers therefore the **integration and interoperability** of systems can be viewed as a key requirement. An extension of the integration and interoperability of systems capability is **collaboration and cooperation** involving ability to support resource and information sharing among managers, workers, and systems. **Predictability and autonomy** aids in the flexibility of PPC in HMLV manufacturing environment. Planning and control systems are required to act autonomously and have the ability to predict and react to manufacturing events and customer demands. Other capability requirements that enhance production flexibility and business sustainability include but not limited to the following: **Distributed PPC**: Ability to decentralize PPC to manage distributed manufacturing environments. **Big data-driven**: Ability of PPC to extract, load, transform and embed data for use of learning, analytics, and event-based decision making. **Accuracy**: Precise decision making and operation. **Context Awareness**: Ability to properly manage machine to machine communication as well as machine to human communications and vice versa. [1-6, 8, 9, 11, 14, 16, 18, 19, 21, 26, 28-33, 38, 40-48]

The range of capabilities described in above are required in various aspects of Production Planning and Control (PPC). In most cases, to achieve effectiveness and/or efficiency in the any single activities/tasks of PPC, it may require two or more of the capabilities discussed above. In production management, the required tasks or aspect of PPC are not identical across board; It may vary based on several factors such as industry type, product types, location, size etc.

2.3. Multi-criteria decision-making (MCDM)

MCDM involves the determination of the best alternative among multiple, conflicting, and interactive criteria which are often correlated [49]. In this section we shall discuss some MCDM methods which, if applied by production managers, can streamline a wide range of decision-making activities.

2.3.1 Analytic Hierarchy Process (AHP)

Analytic Hierarchy Process (AHP) was developed in the 1970s by Thomas L. Saaty. It is typically used in decision making for complex scenarios, where people work together to make decisions when human perceptions, judgments, and consequences have long-term repercussions. The multi-criteria programming made using the AHP is a technique for decision making in complex environments in which many variables or criteria are considered in the prioritization and selection of alternatives or projects. The AHP has a focus on departure from consistency, its measurement and on dependence within and between the groups of elements of its structure. One of the widest applications of AHP is in planning and resource allocation [45, 49, 50].

In AHP, a hierarchy or network structure is required to represent a problem and pairwise comparison is used to establish relations within the structure. This comparison may use concrete data from the alternatives or human judgments to input additional information. The steps involved in AHP can be summarized as follows:

Decompose problem into hierarchy of criteria having the goal at the top level, attributes at the second level and alternatives at the third level.

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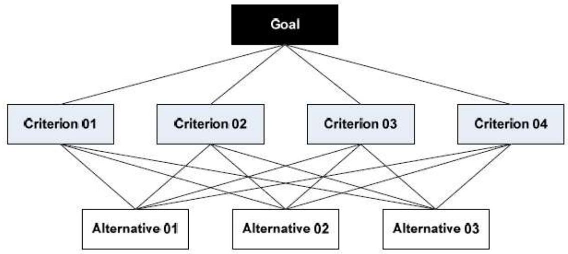

Figure 3: Hierarchy of objectives [51]

I. Determine the relative importance of different attributes or Criteria with respect to the goal using pair-wise comparison matrix. Also create a scale of relative importance to aid this.
II. Calculate the normalized pairwise matrix by dividing all the elements of the column by the sum of the column.
III. Calculate the criteria weight by averaging all the elements in the rows
IV. Calculate the consistency by multiplying each value in the column of the un-normalized matrix by the criteria weight
V. Calculate the weighted sum value by taking the sum of each valued in the rows of result in v.
VI. Determine the ratio between the weighted sum value and the criteria weight.
VII. Calculate λ_{max} by taking the average of the ratios derived in vii.
VIII. Calculate the consistency index (CI) = $\frac{(\lambda max- \ )}{n-1}$
IX. Calculate the consistency ratio by dividing the consistency ratio by random index. (Using random consistency index table)
X. If consistency ratio is less than the standard 0.10, then you can assume that your matrix is reasonably consistent.

After calculating the weight of the criteria and determining that it has appropriate consistency level (as outlined in steps i – xi) you can then proceed with the decision making using the hierarchies for further calculation as outlined in subsequent steps

Compare the alternatives with each other with respect to criterion 1 and repeat steps with all other criterions. After performing this comparison, priority level of all the alternatives can them be deduced from the results. One of the major setbacks of the AHP is that it does not allow for the measurement of the possible dependencies among factors. This setback is handled with the introduction of the Analytical Network Process which is discussed in next section of this literature.

2.3.2. Analytical network process (ANP)

This is an extension of the Analytical Hierarchy process. it is more comprehensive and can be viewed as a generalization of the AHP method. The ANP has wide applications in various areas such as supply chain management, waste management, energy, construction, risk assessment and healthcare. It proves to be an effective decision-making methodology [52].

The ANP captures the dependency and feedback among the different elements in the decision model; it takes into consideration the dependency among elements in same cluster (inner dependency) and the dependency among element in different cluster (outer dependency) to prioritize alternatives [53]. Therefore, ANP can model complex decision problems where the hierarchical model, as used in the ANP is not sufficient. In this literature, we shall discuss the general implementation of AHP while acknowledging the best practices to verify model assumptions prior to analysis, during analysis and reporting of results.

As mentioned earlier, the AHP is incorporated in the ANP therefore, in the process on performing the ANP analysis, you will have to perform the same AHP activities and

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more. To move from the hierarchical model to the network model, we take into consideration the impact of alternatives on the importance of criteria. First, compare all the criteria with respect to each of the alternative (This will enable the identification of the outstanding qualities of each alternative). After this comparison, arrange the corresponding weights into the super-matrix, we get the unweighted super-matrix of the network model. The matrix is then normalized (i.e., the sum of all columns is scaled to 1) resulting in the weighted super-matrix. The whole model is then synthesized by calculating the "Limit Matrix". The limit matrix is the weighted Super-Matrix taken to the power of k+1, where k is an arbitrary number. This results to the ranking of the alternatives in the network model. In ANP, it is possible for the importance of criteria to change based on the available alternatives unlike in the AHP [54].

In the ANP model, we can have a control hierarchy where there are multiple layers with sub-networks as shown in the example Figure 4 below:

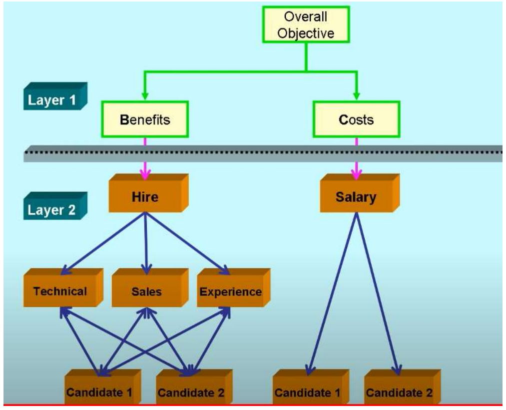

Figure 4: Control Hierarchy Decision network [54]

We have a two-layer model with a control hierarchy (benefits and costs) and a sub-network under benefits and hierarchy under costs. Ranking in of alternatives in a two-layer model as shown in this example can be evaluated using a ratio formular between benefit and cost or an additive formular benefit – cost. The control hierarchy could even be extended with additional control parameters and appropriate mathematical formular is then used to evaluate the ranking of the alternatives.

Enrique Mu, in his article on "Best practices in Analytic Network Process studies" outlines the best practice requirements in various aspects of the ANP process and reporting used for validation purposes [53]. These include

Influence Matrix: which allows one to easily identify which elements are interdependent, as well as potential absorbing states.

Pairwise Comparison Matrix Consistency: It is vital to indicate consistency ratio of any pairwise comparison that is done.

Cluster Comparison Matrix: It is necessary to provide cluster comparison matrix for each network. This can be used together with the weighted super-matrix to see what level of dependency was captured as the cluster weights were applied and how column normalization was obtained.

Limit Matrix: It is good to always report the limit super-matrix and not just the final priorities of interest. This helps with result verification.

Weighted Super-matrix: This contains a lot of information and detailed reporting on this will enhance the result verification process.

Sensitivity Analysis: It is important to examine how robust the decision is. The sensitivity analysis within each subnetwork may be done at the level of the criteria clusters or even at the level of an individual criterion. While the type and extent of the sensitivity

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analysis will vary from study to study, it is necessary to discuss the sensitivity approach that was followed and explain why those specific analyses were important.

Rating scale: it is important to report the rating scales for each criterion, particularly if there have been different scales used for the different criteria. As much as possible, set the rating scales using mathematical models or as objective as possible.

2.3.3. Data Envelopment Analysis

Another form of multi-criteria decision-making methodology is the use of "Data Envelopment Analysis" model. It is a mathematical programming approach used to measure productive efficiency, based on the idea of the production frontier in micro-economics [55]. Although DEA has a strong link to production theory in economics, the tool is also used for benchmarking in operations management, where a set of measures is selected to benchmark the performance of manufacturing and service operations. In benchmarking, the efficient DMUs, as defined by DEA, may not necessarily form a "production frontier", but rather lead to a "best-practice frontier" [56].

DEA has various applications such as in performance evaluations, cost benefit analysis etc. However, we shall discuss it in the context its application in multi-criteria decision-making. The DEA is used to measure the performance efficiency of set of entities or alternatives also known as Decision Making Units (DMU). To explain the concept of DEA, we shall use a combination of existing literatures in the topic and arbitrary data example for clarification of the concepts. We shall be using the CCR model of DEA which is based linear programing as developed by Charnes in 1978 [56].

The sample in table/matrix below, shows the attributes of different gaming console alternatives. These alternatives can be regarded as decision making units (DMU) 1 to 4.

		Attribute or Criteria				
		Price ($)	Storage (GB)	Camera (MP)	Screen thickness (mm)	
Alternatives	Console 1	250	16	12	4	DMU-1
	Console 2	225	16	8	5	DMU-2
	Console 3	300	32	16	4.5	DMU-3
	Console 4	275	32	8	4	DMU-4

Table 1: Specifications for different gaming consoles laptops

The DEA model employs the concept of system efficiency which uses output or input to determine the overall efficiency of a DMU. The non-beneficial criteria are classified as inputs, in this case 'Price' while the beneficial criteria are classified as outputs i.e., 'storage', 'camera' and 'screen thickness'. A DMU is considered to be inefficient if it fails to attain maximum output with minimum input.

The first step I the evaluation is to normalize the matrix using the formula below

$$N_{ij} = \frac{X_{ij}}{\sqrt{\sum_{j=1}^{n} X^2{}_{ij}}}$$

This results to

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		Price ($)	Storage (GB)	Camera (MP)	Screen thickness (mm)
Alternatives	Console 1	0.4735	0.3162	0.5222	0.4551
	Console 2	0.4262	0.3162	0.3482	0.5689
	Console 3	0.5682	0.6325	0.6963	0.5120
	Console 4	0.5209	0.6325	0.3482	0.4551

Table 2: Normalized matrix

Given that the basic fractional CCR model is a non- convex programming which is very tough to compute, the linear programming method developed by Charnes in 1978 makes computations easier and it is articulated either by maximizing the output or minimizing the input criteria. The formular is

$$g_k = \min \left(\sum_{i=1}^{m} v_i . x_{ik} \right)$$

$$H_k = \frac{1}{g_k}$$

Subject to the following constraints

$$-\sum_{r=1}^{s} u_r y_{rk} + \sum_{i=1}^{m} v_i xik \quad \geq 0 \; for \; j = 1, \ldots, n$$

$$\sum_{r=1}^{s} u_r y_{rk} = 1$$

$u_r \geq 1$, r = 1,…., s and $v_r \geq 0$, i=1,….,m
n = number of alternatives (DMUs)
m = number of input criteria
s = number of output criteria
x_{ik} and y_{rk} denotes the values of the i^{th} input criterion and r^{th} output criterion for kth alternative (inputs and outputs)
u_r and v_r are the non-negative variable weights to be determined by the solution of the minimization problem.

If evaluate the first DMU (console 1), we have the objective function as
g1 = min(0.4735V1)
subject to constraints

$$\left.\begin{aligned} &- 0.3162u_1 - 0.5222u_2 - 0.4551u_3 + 0.4735V_1 \geq 0 \\ &- 0.3162u_1 - 0.3482u_2 - 0.5689u_3 + 0.4262V_1 \geq 0 \\ &- 0.6325u1 - 0.6963u_2 - 0.5120u_3 + 0.5682V_1 \geq 0 \\ &- 0.6325u1 - 0.3482u_2 - 0.4551u_3 + 0.5209V_1 \geq 0 \end{aligned}\right\} \text{Common constraints}$$

With equality constraint of $0.3162u_1 + 0.5222u_2 + 0.4551u_3 = 1$
$u_1, u_2, u_3, v_1 \geq 0$
same is repeated for the other DMU where the common constraints remain the same and the equality constraint and objective function changes as shown below:
$g_2 = \min(0.4262V_1)$ with equality constraint: $0.3162u_1 + 0.3482u_2 + 0.5689u_3 = 1$
$g_3 = \min(0.5682V_1)$ with equality constraint: $0.6325u_1 + 0.6963u_2 + 0.512u_3 = 1$
$g_4 = \min(0.5209V_1)$ with equality constraint: $0.6325u_1 + 0.3482u_2 + 0.4551u_3 = 1$
After outlining all the required equations for the objective functions and constraints, you may now optimize each of the DMU parameters to calculate outputs and outputs (g_k

and H_k) Applications such as math lab or excel can be utilized for such optimization. The solution for our sample shows that consoles 2 3 and 4 are all efficient and anyone of them can be chosen since they have same values in the input criteria and the output criteria. The choices are based on the need to get the maximum output with minimal input.

DEA makes it possible to identify efficient and inefficient units in a framework where results are considered in their context. In addition, DEA also provides information that enables the comparison of each inefficient unit with its "peer group", that is, a group of efficient units that are identical with the units under analysis [57]. To achieve sustainable manufacturing, the DEA approach can be utilized to evaluate productivity from input to output as derived from economic factors. The DEA bad-output model can be used to evaluate the sustainability performance of a manufacturing company [55] .

2.4. Product Development (Quality Function Deployment)

Quality function deployment (QFD) is a method used to help transform customer's expectations, preferences, and aversions (Voice of customer) into engineering characteristics for a product. It was originally developed in Japan in 1966 by Yoji Akao and he described it as a "method to transform qualitative user demands into quantitative parameters, to deploy the functions forming quality, and to deploy methods for achieving the design quality into subsystems and component parts, and ultimately to specific elements of the manufacturing process" [58, 59]. QFD was introduced in the Unites States in the early 1980s by the major auto manufacturers like Ford and General Motors, also some electronics manufacturers used the concept [60].

QFD is used in several sectors ranging from manufacturing, health care and service organizations. In the world of business, every organization has customers who they work towards satisfying their demands and a great approach or tool of choice is the QFD. It is a focused methodology to carefully listen to the voice of customer and effectively respond to their need and expectations. QFD translates customer requirements into measurable design targets and drive them from the assembly level down to the sub assembly, component, and production process controls. The methodology provides a defined set of matrixes utilized to translate these progressions [58, 61, 62].

One of the most important aspects of every organization success is effective communication. It is vital that the Voice of Customer (VOC) is communicated to multiple operations throughout the organizations ranging from design, quality, manufacturing, production, marketing, and sales etc. This allows the entire organization to work together to make a product with very high level of customer perceived value. This is the key benefit of the use of QFD as it is customer focused and provides avenue for direct competitor analysis i.e., it allows for direct comparison of how an organization's design or product compares with competitors in meeting the VOC. Another key benefit of the QFD is short product development time and lower costs because it reduces the likelihood of late design changes by focusing on product features and improvements based on customer requirements [58, 60, 61]. QFD provides a structured method and tools for documenting/recording the decisions made and lessons learned during the product development process which can serve as a historical record for utilization in future projects/products [62].

The QFD methodology can be described as a 4-phase process that encompasses the activities throughout the product development cycle. A series of matrixes are utilized at each phase. The voice of customer is utilized to translate the VOC to design requirements for each system, sub-system, and components. The four phases of QFD are described in Figure 5 below:

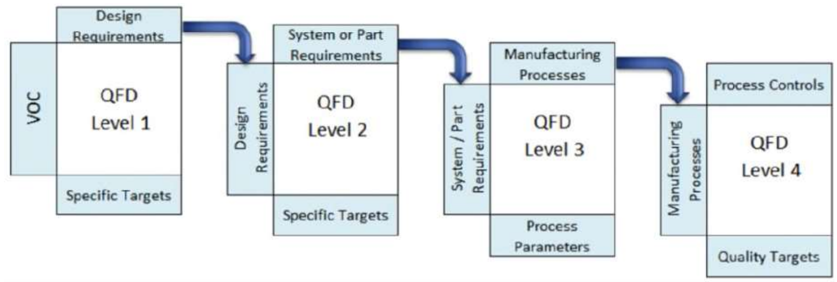

Figure 5: QFD implementation phases

Product Definition: This involves the collection of VOC and translating it into product specifications. Sometimes, it may also involve some form of competitive analysis to evaluate how effectively the existing competitors are fulfilling customer wants and needs. There is also an initial product design concept with specifications and performance. [60, 62, 63].

Product Development: In this phase, the critical parts and assemblies are identified. These product characteristics are cascaded down and translated into critical parts and assembly specifications. Also, the functional requirements for the specification are defined for each functional level [60-62].

Process Development: Here, the manufacturing and assembly processes are designed based on product and component specifications. The process flow is developed, and the critical process characteristics are identified [60, 62].

Process Quality Control: Prior to production launch, process parameters are determined, and the appropriate process controls are developed and implemented. Production only begins after capability studies are done.

The House of Quality (HoQ) is an effective QFD tool that is used to translate the VOC into product or service design characteristics. It utilizes relationship matrixes and is usually the first matrix used in the QFD process [59]. Figure 6 shows the HoQ with its key sections.

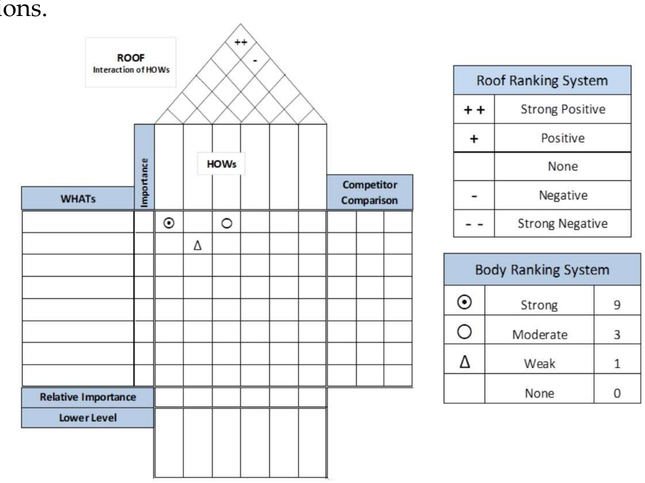

Figure 6: QFD House of Quality [63]

The HoQ demonstrated the relationships between the customer wants i.e., the “WHATs” section in Figure 6 and the design parameters i.e., the “HOWs”. The matrix is data intensive and allows the capture of large amount of information in one place. HoQ’s name is derived from its structure resembling that of a house [63].

Level 1 QFD:

The “WHATs” section of the level 1 HoQ is usually the first section to be determined. This is where the VOC are listed. There are various tools and techniques used to determine

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the VOC ranging from observation, interview, questionnaire, database, checklists etc. The outlined functions from the VOC are ranked based on their level of importance to the customer using appropriate scales of importance [62, 63]. The "HOWs" section (also known as Ceiling) contains the design features and/or technical requirements of the product to align with the VOC. The body of the HOW-WHAT matrix is where the "Hows" are ranked according to their correlation in fulfilling each of the "Whats". Ranking systems are used is a set of symbols which indicates either strong, moderate, weak or no correlation. The table in Figure 6 titled "Body Ranking System" show the ranking symbols and their corresponding values. The "Roof" matrix is used to indicates the level of interrelationship between the design requirements. The rating for the roof matrix ranges from strong positive to strong negative as shown in "Roof Ranking System" table in Figure 6. There is also a competitor comparison which visualized a comparison between our products and other competitor products in the context of how they fulfil the customer requirement. This section should be filled out using mainly direct feedback from customers. The relative importance section is derived by sum-product of the value of each column and the importance factor. These can be represented as discreet number or a percentage of total; it is useful for ranking each of the "Hows" to identify where to allocate most of the resources. The lower level or foundation lists more specific target values for technical specifications relating to the "Hows" that are used to satisfy he VOC. The data from the foundation is deployed to appropriate teams within the organization and it populated into the HoQ for the level 2 QFD [58-64].

3. Methods

3.1. Problem statement

The advent of the Fourth industrial revolution has led to the emanation of new fronts for competitiveness, strategy and productivity in industrial processes and manufacturing. The flexibility of production planning and control plays a vital role in a business's ability to meet demands, stay viable and differentiate itself from competitors.

Environmental, Social, Political and Economic factors are having increasing impacts on industry operations. However, with globalization and the exponential pace of technological advancements have introduced various areas of opportunities for industries. Businesses are seeking to take advantage of these opportunities to implement various computer-aided systems and industry 4.0 concepts that will tackle various aspects of their operations to achieve production flexibility which in turn provides key sustainability qualities.

Computer-aided Production flexibility, if achieved and optimized, can promote key aspects of business including:

High availability: Production is up and running for long periods of time, with little or no unplanned downtime.

Elasticity and Scalability: Ability to automatically or dynamically increase or decrease resources as needed for any given workload

Agility and Fault tolerance: Ability to react quickly with minimal human intervention and remain up and running in the event of a component/process failure or malfunction.

Disaster recovery: Capability to quickly recover from catastrophic events that occur that may seriously affect the business.

The focus point of this study is the identification of key industry 4.0 attributes (computer-aided systems) that are implemented in production planning/control, subsequent deduction of the requirements to achieve production flexibility in manufacturing industries and the level of impact it has on sustainability.

3.2. Objectives

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The aim of the research is to discuss the various segments of typical manufacturing life cycle and their corresponding digital manufacturing tools, outline the outline the industry 4.0 technological requirements the respective tools and finally identify the level of impact it has in achieving production flexibility that promotes business sustainability.

3.3. Research Questions

- ✓ What are the smart requirements in production planning and control that promote flexibility?
- ✓ What kind of computer-aided systems (Industry 4.0 technological concepts) can be integrated for production management?
- ✓ What are the most effective technological concepts for providing the smart capability requirements identified in 1 above?
- ✓ How does production flexibility promote business sustainability in areas of availability, elasticity/scalability, agility/fault tolerance and disaster recovery?

3.4. Conceptualization

Industry 4.0: This refers to the fourth industrial revolution; centering on the integration of business, information technology and engineering processes. It provides digital solutions for the automation of manufacturing. [4, 6, 9, 10]
Digitalized manufacturing: This implies the integration of computational intelligence, automation, robotics, additive manufacturing, and human-machine interaction in the process of manufacturing. [4]
Production flexibility: Ability to easily adapt to and implement changes in the type, quantity and frequency of product being manufactured. [4, 5, 7, 44]
Computer-aided systems: This refers to the concepts and technologies of industry 4.0 such as digital simulation, autonomous robots, cloud computing, Internet of Things, Big Data & Analytics, Augmented Reality, Cyber security etc. [4, 9]
Sustainability: This refers to business sustainability involving the ability of industries to possess capabilities such as high availability, elasticity, scalability, agility, fault tolerance and disaster recovery. [5, 45]

4. Results

In the previous sections, we identified key capabilities which are required that promote smart and flexible production planning and control in HMLV manufacturing environment. We also identified the industry 4.0 concepts that are applicable in a wide range of manufacturing industries. In this section, we shall use content-analysis based approach to outline and rank the smart requirements for production planning and control that promote flexibility and the level of impact the industry 4.0 concepts have in providing these smart capability requirements.
The capabilities and industry-4.0 concepts as identified are outlined below:

Capabilities:

- C-1. Real-Time
- C-2. Adaptability and Dynamic
- C-3. Visibility and traceability
- C-4. Synchronization
- C-5. Autonomy
- C-6. Predictability
- C-7. Integration and Interoperability of systems
- C-8. Scalability and Reconfiguration
- C-9. Distributed PPC
- C-10. Collaboration and Cooperation
- C-11. Mass Customization

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C-12. Big data-driven
C-13. Accuracy
C-14. Context Awareness

Industry 4.0 Concepts:

A-1. Cyber-Physical Systems (CPS)
A-2. Cloud Computing
A-3. Internet of Things (IoT)
A-4. Big Data and Analytics/ Artificial Intelligence (BDA/AI)
A-5. Additive Manufacturing (AM)
A-6. Simulation
A-7. Cybersecurity
A-8. Mobile Technologies
A-9. Adaptive Robotics

Using the Analytical Hierarchy Process multi-criteria decision-making approach, we can group the aspects of the evaluation using the below:

Goal = Production Flexibility
Criteria = PPC Capabilities
Alternatives = Industry 4.0 technologies

The criteria can be broken down into further levels i.e., sub-criteria based on specific industry and/or specific PPC to conduct the analysis in a more granular level. However, for the purpose of this study, we shall limit the hierarchy of the AHP to just 3 levels as shown in figure13 below. (For readability, not all criteria and alternatives are designed in the hierarchy, rather they are outlined by the right side.)

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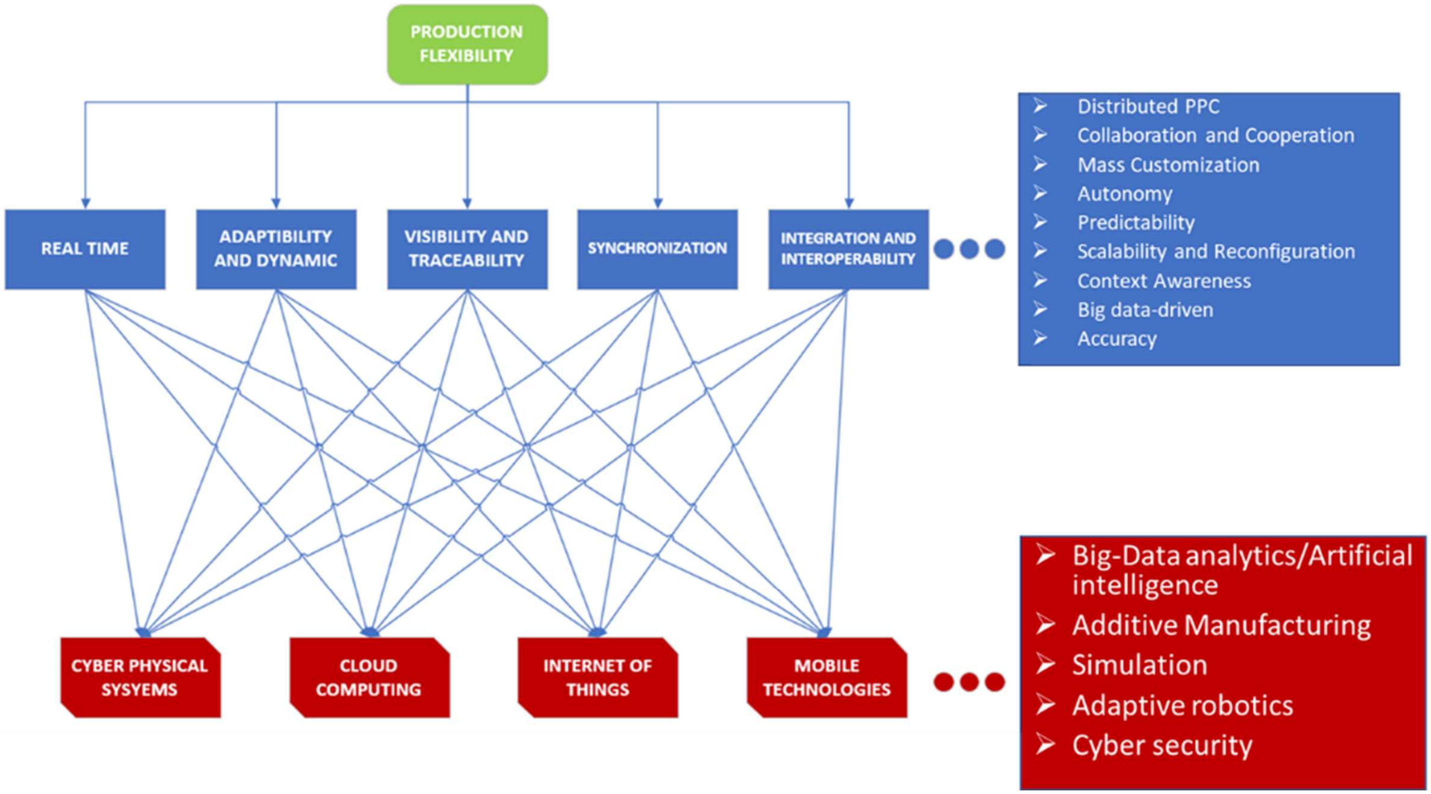
1



2

Figure 7: Hierarchy of criteria/objectives [Author's Work] 3

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	CAPABILITY REQUIREMENTS REFERENCED PER ARTICLE													
	Real-Time	Adaptability and Dynamic	Visibility and traceability	Synchronization	Autonomy	Predictability	Integration and Interoperability of systems	Scalability and Reconfiguration	Distributed PPC	Collaboration and Cooperation	Mass Customization	Big data-driven	Accuracy	Context Awareness
	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14
(Qin, Liu, and Grosvenor 173-178)				1	1			1			1			
(Manavalan and Jayakrishna 925-953)	1	1	1	1	1		1	1	1	1		1	1	1
(Craveiro et al. 251-267)		1		1	1		1	1	1		1		1	1
(Rojo Gallego Burin, Perez-Arostegui, and Llorens-Montes 100610)	1		1	1		1			1	1		1		
(Hansen and Bøgh)	1	1	1	1	1	1	1			1		1	1	1
(Singh)	1		1			1	1	1		1	1	1	1	1
(Messner et al. 689-694)	1		1	1		1	1	1		1	1			
(Gaub 401-404)		1					1	1	1		1		1	
(Gallego García and García García)	1	1	1	1	1	1	1	1	1	1	1	1	1	1
(Van Dierdonck and Miller 37-46)	1	1	1	1	1	1	1	1	1	1	1	1	1	
(Jaskó et al. 103300)	1	1	1	1	1	1	1	1				1		1
(Héctor, Luis, and Sánchez)	1	1	1	1	1	1	1	1	1	1	1	1	1	1
(Jauregui Becker, Borst, and van der Veen 419-422)			1	1		1	1	1	1	1		1	1	
(García and García 415)	1	1	1	1	1	1	1	1	1	1	1	1	1	1
(Machado et al. 1113)		1	1	1			1			1		1		
(Innovapptive)	1	1	1	1	1	1	1	1	1	1	1	1	1	1
(ISO and ASTM-international)					1			1	1		1			
(Silva, Elias Ribeiro da et al. 174)	1	1	1	1	1	1	1	1	1	1	1	1	1	1
(William J Stevenson)		1	1	1			1	1				1	1	
(Müller, Veile, and Voigt 106733)	1	1	1	1	1	1	1	1	1	1	1	1	1	1
(Kocsi et al.)	1		1	1		1	1					1	1	
(Silva, Elias Hans Dener Ribeiro da et al. 240)	1	1	1	1	1	1	1	1	1	1	1	1	1	1
(Schumacher, Nemeth, and Sihn 409)	1	1	1	1	1	1	1	1	1	1	1	1	1	1
(Litster and Bogle 1003)	1	1	1	1	1	1	1	1		1	1	1	1	1
(Bueno, Filho, and Frank 106774)	1	1	1	1	1	1	1	1		1		1	1	
(KIEL et al. 1740015)		1	1	1			1			1		1		
(Delic and Eyers 107689)		1			1		1	1	1		1		1	1
(Ojstersek and Buchmeister)	1	1	1	1		1	1	1		1		1		
(Dilberoglu et al. 545-554)		1	1	1	1		1	1			1		1	1
(Ming-wei and Shi-lian 151)			1	1			1	1	1	1		1	1	
(Wall et al. 1)	1						1					1		
(Shang and You 1010-1016)	1	1	1	1	1	1	1	1		1	1	1	1	1
(Rossit, Tohmé, and Frutos 2164)	1			1	1		1					1		
(Wu, Huang, and Yang 143)	1	1	1	1	1	1	1	1	1		1	1	1	1
TOTAL	23	24	27	29	22	21	31	27	18	22	20	27	24	18

Table 3: Articles discussing various kinds of requirements for production flexibility (Authors own compilation)
4
5

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To minimize the level of subjectivity in conducting the pairwise comparison of the criteria, we use Table 3 which shows the list of articles from various scientific databases that identified the capabilities discussed in the literature review as requirements for production flexibility. It can be seen that "Integration and Interoperability of Systems" is identified in 31 of the articles out of the 34 articles reviewed while capabilities like "Context awareness" and "Distributed PPC" had the least number of articles that identified them. This table will form the basis of the objectivity in assigning importance index for the purpose of the AHP decision-making analysis.

First, we determine the percentage reference which is

$$Reference\ Ratio = \frac{C_n}{T}$$

Equation 1

Where C_n = total number of articles that cited the capability and T is total number of articles reviewed.

This gives:

Capability	Ref_Ratio
C-1	0.676471
C-2	0.705882
C-3	0.794118
C-4	0.852941
C-5	0.647059
C-6	0.617647
C-7	0.911765
C-8	0.794118
C-9	0.529412
C-10	0.647059
C-11	0.588235
C-12	0.794118
C-13	0.705882
C-14	0.529412

Table 4: Reference ratio of capabilities (Author's Work)

Then we calculate the reference ratio for each capability with other capabilities as shown in Table 17 in the appendix A. The rows are subtracted from the column therefore the positive values indicate that the row item is referenced in more articles than the column items by that percentage of articles while the negative values indicate less.

To apply this 'reference ratio' into the Saaty's scale of relative importance, we apply conditions for each assignment as representation as shown in the table below:

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Scale of relative importance		**Condition for reference ratio**
Equal Importance	1	0 to 10%
Weak/light	2	>10% and <=20%
Moderate Importance	3	>20% and <=30%
Moderate Plus	4	>30% and <=40%
Strong Importance	5	>40% and <= 50%
Strong Plus	6	>50% and <=60%
Very Strong Importance	7	>60% and <= 70%
Very, very Importance	8	>70% and <=80%
Extreme Importance	9	>80%

Table 5: Scale of importance

Using the scale in Table 5 above, we conduct the pairwise comparison of the criteria resulting to Table below. The B-Box software application is used for conduction the AHP analysis.

On Standardizing the importance (see Table 7) we see the ranking of the various criteria as it relates to the requirements for the goal of flexibility in manufacturing. 'Integration and interoperability of systems' rank the highest followed by, 'synchronization', 'visibility/traceability' and 'scalability/reconfiguration'. Although, also required for production flexibility (as discussed in the literature review); 'context awareness', 'distribute PPC' and predictability ranked lowest, and this may be attributed to the fact that they highly depend on the existence of the other capabilities.

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Criteria	Real-Time	Adaptability and Dynamic	Visibility and traceability	Synchronization	Autonomy	Predictability	Integration and Interoperability of systems	Scalability and Reconfiguration	Distributed PPC	Collaboration and Cooperation	Mass Customization	Big data-driven	Accuracy	Context Awareness
Real-Time	1	1	1/2	1/2	1	1	1/3	1/2	2	1	1	1/2	1	2
Adaptability and Dynamic	1	1	1	1/2	1	1	1/3	1	2	1	2	1	1	2
Visibility and traceability	2	1	1	1	2	2	1/2	1	3	2	3	1	1	3
Synchronization	2	2	1	1	3	3	1	1	3	3	1/3	1	2	4
Autonomy	1	1	1/2	1/3	1	1	1/3	1/2	2	1	1	1/2	1	2
Predictability	1	1	1/2	1/3	1	1	1/3	1/2	1	1	1	1/2	1	1
Integration and Interoperability of systems	3	3	2	1	3	3	1	2	4	3	4	2	2	4
Scalability and Reconfiguration	2	1	1	1	2	2	1/2	1	3	2	3	1	1	3
Distributed PPC	1/2	1/2	1/3	1/3	1/2	1	1/4	1/3	1	1/2	1	1/3	1/2	1
Collaboration and Cooperation	1	1	1/2	1/3	1	1	1/3	1/2	2	1	1	1/2	1	2
Mass Customization	1	1/2	1/3	3	1	1	1/4	1/3	1	1	1	1/3	1/2	2
Big data-driven	2	1	1	1	2	2	1/2	1	3	2	3	1	1	3
Accuracy	1	1	1	1/2	1	1	1/2	1	2	1	2	1	1	2
Context Awareness	1/2	1/2	1/3	1/4	1/2	1	1/4	1/3	1	1/2	1/2	1/3	1/2	1

Table 6: Pairwise Matrix Comparison of the criteria [Author's Work]

Crieria	Real-Time	Adaptability and Dynamic	Visibility and traceability	Synchronization	Autonomy	Predictability	Integration and Interoperability of systems	Scalability and Reconfiguration	Distributed PPC	Collaboration and Cooperation	Mass Customization	Big data-driven	Accuracy	Context Awareness	Relative importance	Rank
Real-Time	0.053	0.065	0.045	0.045	0.050	0.048	0.052	0.045	0.067	0.050	0.042	0.045	0.069	0.063	0.053	9
Adaptability and Dynamic	0.053	0.065	0.091	0.045	0.050	0.048	0.052	0.091	0.067	0.050	0.084	0.091	0.069	0.063	0.065	7
Visibility and traceability	0.105	0.065	0.091	0.090	0.100	0.095	0.078	0.091	0.100	0.100	0.126	0.091	0.069	0.094	0.092	3
Synchronization	0.105	0.129	0.091	0.090	0.150	0.143	0.156	0.091	0.100	0.150	0.014	0.091	0.138	0.125	0.112	2
Autonomy	0.053	0.065	0.045	0.030	0.050	0.048	0.052	0.045	0.067	0.050	0.042	0.045	0.069	0.063	0.052	10
Predictability	0.053	0.065	0.045	0.030	0.050	0.048	0.052	0.045	0.033	0.050	0.042	0.045	0.069	0.031	0.047	12
Integration and Interoperability of systems	0.158	0.194	0.182	0.090	0.150	0.143	0.156	0.182	0.133	0.150	0.168	0.182	0.138	0.125	0.154	1
Scalability and Reconfiguration	0.105	0.065	0.091	0.090	0.100	0.095	0.078	0.091	0.100	0.100	0.126	0.091	0.069	0.094	0.092	3
Distributed PPC	0.026	0.032	0.030	0.030	0.025	0.048	0.039	0.030	0.033	0.025	0.042	0.030	0.034	0.031	0.033	13
Collaboration and Cooperation	0.053	0.065	0.045	0.030	0.050	0.048	0.052	0.045	0.067	0.050	0.042	0.045	0.069	0.063	0.052	10
Mass Customization	0.053	0.032	0.030	0.271	0.050	0.048	0.039	0.030	0.033	0.050	0.042	0.030	0.034	0.063	0.058	8
Big data-driven	0.105	0.065	0.091	0.090	0.100	0.095	0.078	0.091	0.100	0.100	0.126	0.091	0.069	0.094	0.092	3
Accuracy	0.053	0.065	0.091	0.045	0.050	0.048	0.078	0.091	0.067	0.050	0.084	0.091	0.069	0.063	0.067	6
Context Awareness	0.026	0.032	0.030	0.023	0.025	0.048	0.039	0.030	0.033	0.025	0.021	0.030	0.034	0.031	0.031	14
sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	

Table 7: Standardization of Criteria Importance [Author's Work]

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The consistency ratio of the criteria shows that the methodology used for the comparison of the input data is consistent. See results for the consistency test below.

Criteria	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Real-Time	0.053	0.766	14.526	0.040
Adaptability and Dynamic	0.065	0.962	14.697	0.054
Visibility and traceability	0.092	1.368	14.794	0.061
Synchronization	0.112	1.605	14.287	0.022
Autonomy	0.052	0.747	14.466	0.036
Predictability	0.047	0.684	14.539	0.041
Integration and Interoperability of systems	0.154	2.244	14.614	0.047
Scalability and Reconfiguration	0.092	1.368	14.794	0.061
Distributed PPC	0.033	0.481	14.717	0.055
Collaboration and Cooperation	0.052	0.747	14.466	0.036
Mass Customization	0.058	0.889	15.451	0.112
Big data-driven	0.092	1.368	14.794	0.061
Accuracy	0.067	0.988	14.672	0.052
Context Awareness	0.031	0.442	14.450	0.035
			Consistency index average (CI)	0.051
			Consistency ratio (CR)	0.032

Table 8: Consistency test on the criteria

Having ranked the smart capability requirements, the AHP analysis proceeds to evaluate the respective industry 4.0 concepts on how well they can help industries exhibit these capabilities. The pairwise comparison conducted for the alternatives shows consistency in the data for all criteria hence this was used for subsequent assignment of relative importance to the alternatives (See Table 18 to Table 23). The ranking resulting from the AHP analysis is as shown in Table 9 below. Internet of Things has a weighting of 1.81 followed closely by Cyber-Physical system with 1.76 weight to rank number 1 and 2 respectively. On the other hand, Cybersecurity ranked lowest amongst all the technologies.

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Items	Real-Time	Adaptability and Dynamic	Visibility and traceability	Synchronization	Autonomy	Predictability	Integration and Interoperability of systems	Scalability and Reconfiguration	Distributed PPC	Collaboration and Cooperation	Mass Customization	Big data-driven	Accuracy	Context Awareness	Total	RANK
Cyber-Physical Systems	0.219	0.160	0.228	0.246	0.205	0.073	0.214	0.166	0.206	0.109	0.050	0.131	0.121	0.252	0.176	2
Cloud Computing	0.113	0.108	0.099	0.052	0.081	0.194	0.066	0.039	0.116	0.077	0.051	0.196	0.121	0.057	0.094	5
Internet of Things	0.219	0.179	0.214	0.209	0.205	0.099	0.266	0.166	0.111	0.143	0.170	0.093	0.112	0.197	0.181	1
Big Data and Analytics/ Artificial Intelligence	0.107	0.076	0.130	0.166	0.055	0.314	0.112	0.038	0.156	0.181	0.051	0.350	0.204	0.132	0.147	3
Additive Manufacturing	0.024	0.061	0.021	0.043	0.100	0.024	0.018	0.343	0.029	0.021	0.312	0.017	0.074	0.034	0.080	6
Simulation	0.067	0.103	0.070	0.067	0.055	0.075	0.056	0.063	0.027	0.037	0.090	0.045	0.112	0.064	0.067	8
Cybersecurity	0.040	0.021	0.051	0.023	0.030	0.037	0.029	0.021	0.082	0.094	0.020	0.032	0.058	0.023	0.037	9
Mobile Technologies	0.147	0.202	0.145	0.113	0.134	0.117	0.164	0.078	0.228	0.302	0.162	0.093	0.095	0.153	0.144	4
Adaptive Robotics	0.064	0.089	0.044	0.080	0.137	0.067	0.076	0.088	0.045	0.035	0.092	0.045	0.104	0.089	0.075	7
weight(e)	0.053	0.065	0.092	0.112	0.052	0.047	0.154	0.092	0.033	0.052	0.058	0.092	0.067	0.031		

Table 9: Rank of the alternatives (Industry 4.0 concepts)

4.1. SURVEY CASE STUDY

The analysis done so far have been based off a literature review approach and the objectivity employed in the AHP analysis discussed above have been based on studies extracted from the work of various authors. However, the respective literatures where information is sourced have their publication date ranging between 1992 and 2020. However, due to the rapid advancement of technology, we shall examine the current application of these I4.0 concepts in today's industries. We shall continue the case study using a survey approach and comparing the results with the ones derived so far.

The survey was conducted between February and March 2021 to gather firsthand information from successful industries across various sectors. The survey was both exploratory and descriptive in nature, aiming to gather current data on industrial status as it relates to their smart capabilities and application of industry 4.0 concepts in their general manufacturing/business operations.

The responses received were from various regions across the world and below is a distribution of the responses by volume with a total of 117 responses.

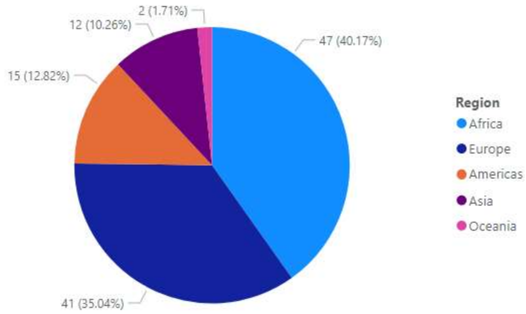

Figure 8: Responses by region

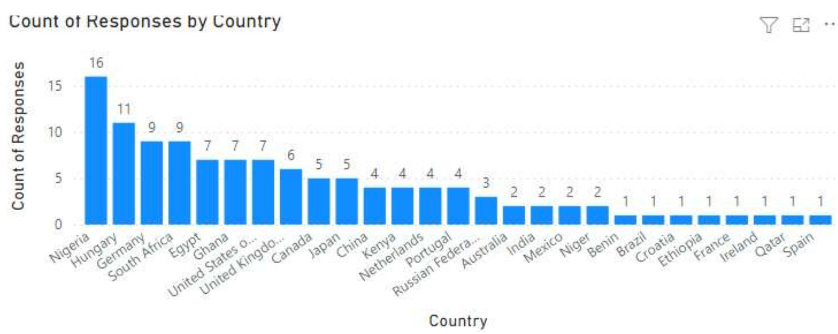

Figure 9: Responses by country.

Although the responses were received from various forms of industries however, the primary target was manufacturing industries therefore 78% of the responses were received from such industries which run some form of HMLV manufacturing environment. Also, the AHP analysis we shall conduct will include only responses from the manufacturing industries while further comparisons and discussions will be done using information derived from the analysis involving the rest of the data.

Assigning ranks to the I4.0 concepts:

The percentage of the industries which utilize the respective I4.0 concepts is as show below:

Cyber-Physical Systems	Cloud Computing	Internet of Things	Big data Analytics/Artificial intelligence	Additive Manufacturing	Simulation	cyber-security	Mobile Technology	Adaptive Robotics
A1	A2	A3	A4	A5	A6	A7	A8	A9
50.43%	**48.72%**	**93.16%**	**82.05%**	**12.82%**	**37.61%**	**43.59%**	**52.14%**	**33.33%**

When we take the average for the comparison of the respective technologies, and factor it into the Saaty's scale of relative importance, we have the pairwise comparison below:

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	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	1	3	1/4	1/3	4	6	2	1/2	4
A2	1/3	1	1/6	1/5	2	3	1/2	1/4	3
A3	4	6	1	2	7	9	4	3	8
A4	3	5	1/2	1	5	8	4	2	7
A5	1/4	1/2	1/7	1/5	1	3	1/3	1/5	2
A6	1/6	1/3	1/9	1/8	1/3	1	1/5	1/7	1/2
A7	1/2	2	1/4	1/4	3	5	1	1/3	3
A8	2	4	1/3	1/2	5	7	3	1	6
A9	1/4	1/3	1/8	1/7	1/2	2	1/3	1/6	1

Table 10: Pairwise comparison derived from survey data

Going forward, for readability, we shall be using A1 to A9 to denote the respective industry 4.0 concepts in tables.

Normalizing the pairwise comparison and calculating for the weight we derive a preliminary ranking as shown in Table 11 below.

	A1	A2	A3	A4	A5	A6	A7	A8	A9	Weight	Rank
A1	0.087	0.135	0.087	0.070	0.144	0.136	0.130	0.066	0.116	0.108	4
A2	0.029	0.045	0.058	0.042	0.072	0.068	0.033	0.033	0.087	0.052	6
A3	0.348	0.271	0.347	0.421	0.251	0.205	0.260	0.395	0.232	0.303	1
A4	0.261	0.226	0.174	0.210	0.180	0.182	0.260	0.263	0.203	0.218	2
A5	0.022	0.023	0.050	0.042	0.036	0.068	0.022	0.026	0.058	0.038	7
A6	0.014	0.015	0.039	0.026	0.012	0.023	0.013	0.019	0.014	0.019	9
A7	0.043	0.090	0.087	0.053	0.108	0.114	0.065	0.044	0.087	0.077	5
A8	0.174	0.180	0.116	0.105	0.180	0.159	0.195	0.132	0.174	0.157	3
A9	0.022	0.015	0.043	0.030	0.018	0.045	0.022	0.022	0.029	0.027	8

Table 11: Preliminary ranking of the alternatives

Note: The above rankings only serve as an aid when calculating for relative importance during the AHP analysis.

A part of the survey was to determine the level of importance attributed to the respective capabilities by the industries and this resulted in the summary score in table below:

	Capability	Average Score from survey
C1	Accuracy	6.155
C2	Adaptability and Dynamic	3.000
C3	Autonomy	10.018
C4	Big data-driven	4.062
C5	Context Awareness	9.563
C6	Distributed PPC	8.765
C7	Integration and interoperability of systems	2.809
C8	Mass Customization	9.158
C9	Predictability	6.957
C10	Real-Time	6.835
C11	Synchronization	5.583
C12	Visibility and traceability	4.115

Table 12: Attributed importance to the capabilities

Applying the same concept as in the literature review approach case study (See Equation 1). However, Cn now denotes number of industries that ranked the concept as vital, and T is the total number of industries that conducted the ranking; we conduct the pairwise comparison of the capabilities resulting in Table 13 (We shall use C1 to C12 to denote the capabilities going forward)

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Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
C1	1	1/2	2	1	2	1	1/3	1	1	2	1	1
C2	2	1	4	1	3	3	1	3	2	1/3	2	1
C3	1/2	1/4	1	1/3	1	1/2	1/4	1	1/2	1/2	1/2	1/3
C4	1	1	3	1	3	2	1/2	2	2	3	1	1
C5	1/2	1/3	1	1/3	1	1/2	1/4	1	1/2	1	1/2	1/3
C6	1	1/3	2	1/2	2	1	1/3	1	1	1	1	1/2
C7	3	1	4	2	4	3	1	3	3	4	2	2
C8	1	1/3	1	1/2	1	1	1/3	1	1	1	1	1/2
C9	1	1/2	2	1/2	2	1	1/3	1	1	1	1	1/2
C10	1/2	3	2	1/3	1	1	1/4	1	1	1	1/2	1/3
C11	1	1/2	2	1	2	1	1/2	1	1	2	1	1
C12	1	1	3	1	3	2	1/2	2	2	3	1	1

Table 13: Pairwise comparison of the Criteria

Table 14 below and Table 24 in appendix A shows the standardization of the importance and the consistency test respectively. This showed that the decision data as derived from the analysis of the survey is consistent therefore, we can proceed with further AHP analysis using the results. The ranking shows "Integration and interoperability of systems" as the most important capability required for production flexibility.

Crieria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	Relative importance	Rank
C1	0.074	0.051	0.074	0.105	0.083	0.059	0.060	0.056	0.061	0.101	0.080	0.105	0.076	6
C2	0.148	0.103	0.148	0.105	0.125	0.176	0.179	0.167	0.121	0.017	0.160	0.105	0.130	2
C3	0.037	0.026	0.037	0.035	0.042	0.029	0.045	0.056	0.030	0.025	0.040	0.035	0.036	12
C4	0.074	0.103	0.111	0.105	0.125	0.118	0.090	0.111	0.121	0.151	0.080	0.105	0.108	3
C5	0.037	0.034	0.037	0.035	0.042	0.029	0.045	0.056	0.061	0.050	0.040	0.035	0.042	11
C6	0.074	0.034	0.074	0.053	0.083	0.059	0.060	0.056	0.061	0.050	0.080	0.053	0.061	8
C7	0.222	0.103	0.148	0.211	0.167	0.176	0.179	0.167	0.182	0.202	0.160	0.211	0.177	1
C8	0.074	0.034	0.037	0.053	0.042	0.059	0.060	0.056	0.061	0.050	0.080	0.053	0.055	10
C9	0.074	0.051	0.074	0.053	0.042	0.059	0.060	0.056	0.061	0.050	0.080	0.053	0.059	9
C10	0.037	0.308	0.074	0.035	0.042	0.059	0.045	0.056	0.061	0.050	0.040	0.035	0.070	7
C11	0.074	0.051	0.074	0.105	0.083	0.059	0.090	0.056	0.061	0.101	0.080	0.105	0.078	5
C12	0.074	0.103	0.111	0.105	0.125	0.118	0.090	0.111	0.121	0.151	0.080	0.105	0.108	3

Table 14: Standardization of importance

Proceeding further, we evaluate the relative importance of the alternatives to have a decision matrix where we rank the alternative based on how important they are at providing the criteria required for production flexibility. Table 25 to 28 in appendix A shows the calculations involved and the consistency for all the alternatives derived from the survey are within the acceptable range.

The decision matrix in Table 15 below shows the weights and ranking of the respective technologies.

Decision Matrix	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	Total Weight	Rank
A1	0.204	0.076	0.055	0.350	0.132	0.156	0.112	0.051	0.314	0.107	0.166	0.130	0.156	3
A2	0.058	0.021	0.030	0.032	0.023	0.082	0.029	0.020	0.037	0.040	0.023	0.051	0.036	9
A3	0.112	0.179	0.205	0.093	0.197	0.111	0.266	0.170	0.099	0.219	0.209	0.214	0.181	1
A4	0.095	0.202	0.134	0.093	0.153	0.228	0.164	0.162	0.117	0.147	0.113	0.145	0.148	4
A5	0.104	0.089	0.137	0.045	0.089	0.045	0.076	0.092	0.067	0.064	0.080	0.044	0.074	6
A6	0.074	0.061	0.100	0.017	0.034	0.029	0.018	0.312	0.024	0.024	0.043	0.021	0.051	8
A7	0.112	0.103	0.055	0.045	0.064	0.027	0.056	0.090	0.075	0.067	0.067	0.070	0.070	7
A8	0.121	0.160	0.205	0.131	0.252	0.206	0.214	0.050	0.073	0.219	0.246	0.228	0.179	2
A9	0.121	0.108	0.081	0.196	0.057	0.116	0.066	0.051	0.194	0.113	0.052	0.099	0.105	5
weight(e)	0.076	0.130	0.036	0.108	0.042	0.061	0.177	0.055	0.059	0.070	0.078	0.108	0.000	

Table 15: Decision matrix

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5. Discussion

In HMLV production environment, there is high level of complexity involved in production planning and control activities. The intricacy of many of the activities including but not limited to production system design, location planning and analysis, facilities and layout, demand forecasting, capacity planning, lot sizing, inventory and supply chain management etc. become more complex; The AHP analysis conducted using both approaches (Literature review and Questionnaire survey) in the case study section identifies Integration and interoperability of systems as the most important capability requirement for production flexibility. However, the ranking of the importance level of other capabilities varies as outlined in Table 7 and Table 14.

Comparing the results of the AHP from both case studies (See Table 9 and Table 15) we can see that there is a significant difference in the ranking of the industry 4.0 importance. Although the Literature review study and the survey study both identifies Internet of things as the most important concept for provision of the capability requirement, we can see the level of importance for most of the other concepts changed. The below table shows the ranking from the two case studies:

Industry 4.0 Concept	Survey Rank	Lit Rev Rank
Cyber-Physical Systems	3	2
Cloud Computing	9	5
Internet of Things	1	1
Big Data and Analytics/ Artificial Intelligence	4	3
Additive Manufacturing	6	6
Simulation	8	8
Cybersecurity	7	9
Mobile Technologies	2	4
Adaptive Robotics	5	7

Table 16: Case study ranking of the alternatives

The survey rank has mobile technologies and cyber-physical system 2nd and 3rd in importance while cloud computing ranked lowest. This is different for the literature review ranking which has cybersecurity as the least important. This discrepancy may be attributed to the fact that the literature review is based on old data and information derived from previous works of authors. However, giving the fast pace of technological advancement and adoption of industry 4.0 concepts in manufacturing industries, the survey analysis presents a more current information on the state of the application of the industry 4.0 technologies and concepts in the manufacturing industry.

Further findings from the survey analysis are outlined below:

- The average number of industry 4.0 concepts used simultaneously by manufacturing companies is 5 but the distribution varies on the type of technology being deployed.
- 93% of manufacturing companies that deploy more than 5 industry 4.0 technological concepts have intercontinental customer base and office locations with more than 250 employees and they have highly decentralized mode of operation.
- Additive manufacturing is the least utilized technology with only 12.8% of the industries having such as part of their manufacturing processes/technologies. The literature shows that this is because the field is relatively new compared to other technologies and therefore the advancements required for widespread adoption with reduced cost implication is still in the early stages. However, for the industries that utilize the technology, the analysis shows that the importance is very high relative to other technological concepts which they deploy. This is evident in one of the comments received in the survey responses from a woodworking manufacturing company in Africa:

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"Although a very expensive addition to the factory, Since the installation of my CNC router, there has been high improvement in the efficiency and output of the company"

- Internet of Things ranked very high in both number of industries that utilize the concept and the level of importance attributed to it. Big data analytics and artificial intelligence followed closely in terms of number industries that use the concept. However, mobile technologies ranked higher at providing the capabilities required for production flexibility and this is evident in the results of the AHP analysis.
- The simple analysis of the responses from the service industries shows that the average number of I4.0 technology concepts simultaneously deployed is 3 and the prevalent concepts are Big data Analytics, Cloud Computing and Cybersecurity. Although this study is focused on manufacturing industries, the same analytical approaches can also be used to determine the ranking of the capability requirement and technological concepts.

6. Conclusions

Production flexibility is paramount for the sustainability of any industry with a high-mix low-volume manufacturing environment. This article conducts a literature review and case study that answers the research questions on smart requirements in production planning and control that promote flexibility Industry 4.0 technological concepts that can be integrated for production management. See page 16

This study also addressed the most effective technological concepts for providing the smart capability requirements. (See discussion above and ranking in Table 15: Decision matrix)

Production flexibility promotes business sustainability in areas of availability, elasticity/scalability, agility/fault tolerance and disaster recovery. The complex calculations and activities involved in the production management lifecycle and operations can easily be handle efficiently and effectively with the use of these industry 4.0 concepts with little trade-offs. With these I4.0 concepts, industries combine multiple scheduling approaches high levels of accuracy and dependability thereby enhancing flexibility. Also, the product development activities discussed in section 1.1 and others can seamlessly run with close to limitless amount of input data from various sources and the manufacturing system will be able to handle and adapt to various scenarios that may come up.

We can also see that Multi-Criteria Decision Making (MCDM) methodologies can provide effective way for industries to determine the best technology implementation required for various aspects of production management. Further research in this field includes Digitalized MCDM systems for Production planning and control with very high levels of objectivity. This study took a broad approach to determine the impact of these technologies. However, it can be developed to target a particular industry type, sector, or operation. For example, forecasting or capacity planning in a specific automotive industry can be handled using one or more MCDM approaches to determine the best combination of technological concepts that will best provide desired results that will serve as inputs to the manufacturing process.

As a further step, a promising approach that may be able to handle complex systems and information flow to dynamically determine best productions approaches is the "Genetic Algorithm". Further studies can be done on the application of genetic algorithm as key aspect in the development of dynamic production scheduling models that enhances sustainability.

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Appendix A

Literature review approach AHP Analysis Tables

	RATIO:	0.676471	0.705882	0.794118	0.852941	0.647059	0.617647	0.911765	0.794118	0.529412	0.647059	0.588235	0.794118	0.705882	0.529412
		C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14
0.676471	C-1		-0.0294	-0.1176	-0.1765	0.0294	0.0588	-0.2353	-0.1176	0.1471	0.0294	0.0882	-0.1176	-0.0294	0.1471
0.705882	C-2	0.0294		-0.0882	-0.1471	0.0588	0.0882	-0.2059	-0.0882	0.1765	0.0588	0.1176	-0.0882	0.0000	0.1765
0.794118	C-3	0.1176	0.0882		-0.0588	0.1471	0.1765	-0.1176	0.0000	0.2647	0.1471	0.2059	0.0000	0.0882	0.2647
0.852941	C-4	0.1765	0.1471	0.0588		0.2059	0.2353	-0.0588	0.0588	0.3235	0.2059	0.2647	0.0588	0.1471	0.3235
0.647059	C-5	-0.0294	-0.0588	-0.1471	-0.2059		0.0294	-0.2647	-0.1471	0.1176	0.0000	0.0588	-0.1471	-0.0588	0.1176
0.617647	C-6	-0.0588	-0.0882	-0.1765	-0.2353	-0.0294		-0.2941	-0.1765	0.0882	-0.0294	0.0294	-0.1765	-0.0882	0.0882
0.911765	C-7	0.2353	0.2059	0.1176	0.0588	0.2647	0.2941		0.1176	0.3824	0.2647	0.3235	0.1176	0.2059	0.3824
0.794118	C-8	0.1176	0.0882	0.0000	-0.0588	0.1471	0.1765	-0.1176		0.2647	0.1471	0.2059	0.0000	0.0882	0.2647
0.529412	C-9	-0.1471	-0.1765	-0.2647	-0.3235	-0.1176	-0.0882	-0.3824	-0.2647		-0.1176	-0.0588	-0.2647	-0.1765	0.0000
0.647059	C-10	-0.0294	-0.0588	-0.1471	-0.2059	0.0000	0.0294	-0.2647	-0.1471	0.1176		0.0588	-0.1471	-0.0588	0.1176
0.588235	C-11	-0.0882	-0.1176	-0.2059	-0.2647	-0.0588	-0.0294	-0.3235	-0.2059	0.0588	-0.0588		-0.2059	-0.1176	0.0588
0.794118	C-12	0.1176	0.0882	0.0000	-0.0588	0.1471	0.1765	-0.1176	0.0000	0.2647	0.1471	0.2059		0.0882	0.2647
0.705882	C-13	0.0294	0.0000	-0.0882	-0.1471	0.0588	0.0882	-0.2059	-0.0882	0.1765	0.0588	0.1176	-0.0882		0.1765
0.529412	C-14	-0.1471	-0.1765	-0.2647	-0.3235	-0.1176	-0.0882	-0.3824	-0.2647	0.0000	-0.1176	-0.0588	-0.2647	-0.1765	

Table 17: Comparison of the ratios of the capabilities (Author's work)

Real-Time	Cyber-Physical Systems	Cloud Computing	Internet of Things	Big Data and Analytics/ Artificial Intelligence	Additive Manufacturing	Simulation	Cybersecurity	Mobile Technologies	Adaptive Robotics	Relative importance
Cyber-Physical Systems	0.241	0.252	0.241	0.255	0.189	0.189	0.152	0.237	0.214	0.219
Cloud Computing	0.080	0.084	0.080	0.028	0.108	0.126	0.114	0.237	0.161	0.113
Internet of Things	0.241	0.252	0.241	0.255	0.189	0.189	0.152	0.237	0.214	0.219
Big Data and Analytics/ Artificial Intelligence	0.080	0.252	0.080	0.085	0.135	0.063	0.152	0.059	0.054	0.107
Additive Manufacturing	0.034	0.021	0.034	0.017	0.027	0.032	0.013	0.024	0.018	0.024
Simulation	0.080	0.042	0.080	0.085	0.054	0.063	0.114	0.030	0.054	0.067
Cybersecurity	0.060	0.028	0.060	0.021	0.081	0.021	0.038	0.030	0.018	0.040
Mobile Technologies	0.121	0.042	0.121	0.170	0.135	0.253	0.152	0.118	0.214	0.147
Adaptive Robotics	0.060	0.028	0.060	0.085	0.081	0.063	0.114	0.030	0.054	0.064

Table 18: Standardized comparison of the technologies (Author's work)

Adaptability and Dynamic	Cyber-Physical Systems	Cloud Computing	Internet of Things	Big Data and Analytics/ Artificial Intelligence	Additive Manufacturing	Simulation	Cybersecurity	Mobile Technologies	Adaptive Robotics	Relative importance
Cyber-Physical Systems	0.181	0.217	0.192	0.171	0.096	0.150	0.116	0.189	0.129	0.160
Cloud Computing	0.090	0.109	0.096	0.057	0.096	0.150	0.116	0.189	0.065	0.108
Internet of Things	0.181	0.217	0.192	0.171	0.241	0.150	0.140	0.189	0.129	0.179
Big Data and Analytics/ Artificial Intelligence	0.060	0.109	0.064	0.057	0.145	0.025	0.116	0.094	0.016	0.076
Additive Manufacturing	0.090	0.054	0.038	0.019	0.048	0.037	0.093	0.038	0.129	0.061
Simulation	0.090	0.054	0.096	0.171	0.096	0.075	0.116	0.038	0.194	0.103
Cybersecurity	0.036	0.022	0.032	0.011	0.012	0.015	0.023	0.027	0.013	0.021
Mobile Technologies	0.181	0.109	0.192	0.114	0.241	0.374	0.163	0.189	0.259	0.202
Adaptive Robotics	0.090	0.109	0.096	0.228	0.024	0.025	0.116	0.047	0.065	0.089

Visibility and traceability	Cyber-Physical Systems	Cloud Computing	Internet of Things	Big Data and Analytics/ Artificial Intelligence	Additive Manufacturing	Simulation	Cybersecurity	Mobile Technologies	Adaptive Robotics	Relative importance
Cyber-Physical Systems	0.248	0.264	0.221	0.229	0.136	0.263	0.162	0.354	0.172	0.228
Cloud Computing	0.083	0.088	0.074	0.114	0.114	0.105	0.121	0.059	0.129	0.099
Internet of Things	0.248	0.264	0.221	0.343	0.136	0.263	0.162	0.118	0.172	0.214
Big Data and Analytics/ Artificial Intelligence	0.124	0.088	0.074	0.114	0.136	0.105	0.162	0.236	0.129	0.130
Additive Manufacturing	0.041	0.018	0.037	0.019	0.023	0.013	0.008	0.017	0.011	0.021
Simulation	0.050	0.044	0.044	0.057	0.091	0.053	0.162	0.039	0.086	0.070
Cybersecurity	0.062	0.029	0.055	0.029	0.114	0.013	0.040	0.029	0.086	0.051
Mobile Technologies	0.083	0.176	0.221	0.057	0.159	0.158	0.162	0.118	0.172	0.145
Adaptive Robotics	0.062	0.029	0.055	0.038	0.091	0.026	0.020	0.029	0.043	0.044

Synchronization	Cyber-Physical Systems	Cloud Computing	Internet of Things	Big Data and Analytics/ Artificial Intelligence	Additive Manufacturing	Simulation	Cybersecurity	Mobile Technologies	Adaptive Robotics	Relative importance
Cyber-Physical Systems	0.283	0.148	0.404	0.301	0.216	0.181	0.158	0.324	0.201	0.246
Cloud Computing	0.094	0.049	0.051	0.050	0.018	0.060	0.105	0.022	0.022	0.052
Internet of Things	0.142	0.198	0.202	0.301	0.180	0.241	0.158	0.259	0.201	0.209
Big Data and Analytics/ Artificial Intelligence	0.142	0.148	0.101	0.150	0.180	0.181	0.132	0.259	0.201	0.166
Additive Manufacturing	0.047	0.099	0.040	0.030	0.036	0.020	0.079	0.016	0.022	0.043
Simulation	0.094	0.049	0.051	0.050	0.108	0.060	0.105	0.022	0.067	0.067
Cybersecurity	0.047	0.012	0.034	0.030	0.012	0.015	0.026	0.013	0.017	0.023
Mobile Technologies	0.057	0.148	0.051	0.038	0.144	0.181	0.132	0.065	0.201	0.113
Adaptive Robotics	0.094	0.148	0.067	0.050	0.108	0.060	0.105	0.022	0.067	0.080

Table 19: Standardized comparison of the technologies cont.

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Autonomy	Cyber-Physical Systems	Cloud Computing	Internet of Things	Big Data and Analytics/ Artificial Intelligence	Additive Manufacturing	Simulation	Cybersecurity	Mobile Technologies	Adaptive Robotics	Relative importance
Cyber-Physical Systems	0.225	0.254	0.225	0.148	0.189	0.148	0.161	0.228	0.267	0.205
Cloud Computing	0.056	0.063	0.056	0.098	0.126	0.098	0.129	0.038	0.067	0.081
Internet of Things	0.225	0.254	0.225	0.148	0.189	0.148	0.161	0.228	0.267	0.205
Big Data and Analytics/ Artificial Intelligence	0.075	0.032	0.075	0.049	0.013	0.049	0.097	0.057	0.044	0.055
Additive Manufacturing	0.075	0.032	0.075	0.246	0.063	0.246	0.065	0.028	0.067	0.100
Simulation	0.075	0.032	0.075	0.049	0.013	0.049	0.097	0.057	0.044	0.055
Cybersecurity	0.045	0.016	0.045	0.016	0.031	0.016	0.032	0.023	0.044	0.030
Mobile Technologies	0.112	0.190	0.112	0.098	0.252	0.098	0.161	0.114	0.067	0.134
Adaptive Robotics	0.112	0.127	0.112	0.148	0.126	0.148	0.097	0.228	0.133	0.137

Predictability	Cyber-Physical Systems	Cloud Computing	Internet of Things	Big Data and Analytics/ Artificial Intelligence	Additive Manufacturing	Simulation	Cybersecurity	Mobile Technologies	Adaptive Robotics	Relative importance
Cyber-Physical Systems	0.055	0.033	0.140	0.061	0.086	0.020	0.110	0.099	0.055	0.073
Cloud Computing	0.275	0.166	0.350	0.122	0.143	0.177	0.146	0.198	0.165	0.194
Internet of Things	0.028	0.033	0.070	0.091	0.143	0.118	0.146	0.099	0.165	0.099
Big Data and Analytics/ Artificial Intelligence	0.330	0.499	0.280	0.365	0.200	0.296	0.183	0.397	0.275	0.314
Additive Manufacturing	0.018	0.033	0.014	0.052	0.029	0.015	0.012	0.025	0.018	0.024
Simulation	0.165	0.055	0.035	0.073	0.114	0.059	0.110	0.033	0.028	0.075
Cybersecurity	0.018	0.042	0.018	0.073	0.086	0.020	0.037	0.025	0.018	0.037
Mobile Technologies	0.055	0.083	0.070	0.091	0.114	0.177	0.146	0.099	0.220	0.117
Adaptive Robotics	0.055	0.055	0.023	0.073	0.086	0.118	0.110	0.025	0.055	0.067

Integration and Interoperability of systems	Cyber-Physical Systems	Cloud Computing	Internet of Things	Big Data and Analytics/ Artificial Intelligence	Additive Manufacturing	Simulation	Cybersecurity	Mobile Technologies	Adaptive Robotics	Relative importance
Cyber-Physical Systems	0.245	0.201	0.290	0.241	0.188	0.195	0.178	0.267	0.119	0.214
Cloud Computing	0.061	0.050	0.058	0.040	0.104	0.098	0.127	0.033	0.020	0.066
Internet of Things	0.245	0.251	0.290	0.321	0.167	0.244	0.178	0.400	0.297	0.266
Big Data and Analytics/ Artificial Intelligence	0.082	0.101	0.072	0.080	0.104	0.195	0.153	0.044	0.178	0.112
Additive Manufacturing	0.027	0.010	0.036	0.016	0.021	0.012	0.006	0.017	0.015	0.018
Simulation	0.061	0.025	0.058	0.020	0.083	0.049	0.102	0.044	0.059	0.056
Cybersecurity	0.035	0.010	0.041	0.013	0.083	0.012	0.025	0.027	0.015	0.029
Mobile Technologies	0.122	0.201	0.097	0.241	0.167	0.146	0.127	0.133	0.238	0.164
Adaptive Robotics	0.122	0.151	0.058	0.027	0.083	0.049	0.102	0.033	0.059	0.076

Table 20:Standardized comparison of the technologies cont.

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Scalability and Reconfiguration	Cyber-Physical Systems	Cloud Computing	Internet of Things	Big Data and Analytics/ Artificial Intelligence	Additive Manufacturing	Simulation	Cybersecurity	Mobile Technologies	Adaptive Robotics	**Relative importance**
Cyber-Physical Systems	0.119	0.183	0.119	0.177	0.080	0.201	0.150	0.232	0.232	0.166
Cloud Computing	0.024	0.037	0.024	0.035	0.067	0.017	0.100	0.019	0.026	0.039
Internet of Things	0.119	0.183	0.119	0.177	0.080	0.201	0.150	0.232	0.232	0.166
Big Data and Analytics/ Artificial Intelligence	0.024	0.037	0.024	0.035	0.057	0.017	0.100	0.019	0.026	0.038
Additive Manufacturing	0.595	0.220	0.595	0.248	0.400	0.251	0.175	0.290	0.310	0.343
Simulation	0.030	0.110	0.030	0.106	0.080	0.050	0.100	0.019	0.039	0.063
Cybersecurity	0.020	0.009	0.020	0.009	0.057	0.013	0.025	0.014	0.019	0.021
Mobile Technologies	0.030	0.110	0.030	0.106	0.080	0.151	0.100	0.058	0.039	0.078
Adaptive Robotics	0.040	0.110	0.040	0.106	0.100	0.100	0.100	0.116	0.077	0.088

Distributed PPC	Cyber-Physical Systems	Cloud Computing	Internet of Things	Big Data and Analytics/ Artificial Intelligence	Additive Manufacturing	Simulation	Cybersecurity	Mobile Technologies	Adaptive Robotics	**Relative importance**
Cyber-Physical Systems	0.209	0.293	0.096	0.141	0.188	0.171	0.166	0.404	0.188	0.206
Cloud Computing	0.052	0.073	0.191	0.070	0.156	0.143	0.166	0.040	0.150	0.116
Internet of Things	0.209	0.037	0.096	0.070	0.063	0.143	0.166	0.067	0.150	0.111
Big Data and Analytics/ Artificial Intelligence	0.209	0.147	0.191	0.141	0.125	0.171	0.166	0.067	0.188	0.156
Additive Manufacturing	0.035	0.015	0.048	0.035	0.031	0.029	0.021	0.034	0.013	0.029
Simulation	0.035	0.015	0.019	0.023	0.031	0.029	0.041	0.034	0.013	0.027
Cybersecurity	0.105	0.037	0.048	0.070	0.125	0.057	0.083	0.101	0.113	0.082
Mobile Technologies	0.105	0.366	0.287	0.422	0.188	0.171	0.166	0.202	0.150	0.228
Adaptive Robotics	0.042	0.018	0.024	0.028	0.094	0.086	0.028	0.051	0.038	0.045

Collaboration and Cooperation	Cyber-Physical Systems	Cloud Computing	Internet of Things	Big Data and Analytics/ Artificial Intelligence	Additive Manufacturing	Simulation	Cybersecurity	Mobile Technologies	Adaptive Robotics	**Relative importance**
Cyber-Physical Systems	0.074	0.113	0.037	0.055	0.136	0.142	0.173	0.071	0.180	0.109
Cloud Computing	0.037	0.056	0.027	0.055	0.114	0.106	0.086	0.059	0.150	0.077
Internet of Things	0.221	0.226	0.110	0.083	0.159	0.177	0.043	0.118	0.150	0.143
Big Data and Analytics/ Artificial Intelligence	0.221	0.169	0.219	0.165	0.159	0.142	0.259	0.118	0.180	0.181
Additive Manufacturing	0.012	0.011	0.016	0.024	0.023	0.009	0.043	0.044	0.008	0.021
Simulation	0.018	0.019	0.022	0.041	0.091	0.035	0.022	0.059	0.030	0.037
Cybersecurity	0.037	0.056	0.219	0.055	0.045	0.142	0.086	0.118	0.090	0.094
Mobile Technologies	0.368	0.338	0.329	0.495	0.182	0.212	0.259	0.354	0.180	0.302
Adaptive Robotics	0.012	0.011	0.022	0.028	0.091	0.035	0.029	0.059	0.030	0.035

Table 21: Standardized comparison of the technologies cont.

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Mass Customization	Cyber-Physical Systems	Cloud Computing	Internet of Things	Big Data and Analytics/ Artificial Intelligence	Additive Manufacturing	Simulation	Cybersecurity	Mobile Technologies	Adaptive Robotics	Relative importance
Cyber-Physical Systems	0.047	0.045	0.046	0.050	0.074	0.023	0.119	0.026	0.021	0.050
Cloud Computing	0.047	0.045	0.069	0.050	0.074	0.017	0.119	0.026	0.015	0.051
Internet of Things	0.142	0.090	0.138	0.149	0.093	0.209	0.143	0.317	0.247	0.170
Big Data and Analytics/ Artificial Intelligence	0.047	0.045	0.046	0.050	0.074	0.035	0.119	0.026	0.021	0.051
Additive Manufacturing	0.236	0.225	0.552	0.248	0.371	0.279	0.167	0.423	0.309	0.312
Simulation	0.142	0.180	0.046	0.099	0.093	0.070	0.095	0.026	0.062	0.090
Cybersecurity	0.009	0.009	0.023	0.010	0.053	0.017	0.024	0.021	0.015	0.020
Mobile Technologies	0.189	0.180	0.046	0.198	0.093	0.279	0.119	0.106	0.247	0.162
Adaptive Robotics	0.142	0.180	0.034	0.149	0.074	0.070	0.095	0.026	0.062	0.092

Big data-driven	Cyber-Physical Systems	Cloud Computing	Internet of Things	Big Data and Analytics/ Artificial Intelligence	Additive Manufacturing	Simulation	Cybersecurity	Mobile Technologies	Adaptive Robotics	Relative importance
Cyber-Physical Systems	0.094	0.065	0.214	0.069	0.130	0.145	0.102	0.214	0.145	0.131
Cloud Computing	0.188	0.131	0.286	0.083	0.152	0.218	0.205	0.286	0.218	0.196
Internet of Things	0.031	0.033	0.071	0.104	0.130	0.145	0.102	0.071	0.145	0.093
Big Data and Analytics/ Artificial Intelligence	0.563	0.654	0.286	0.416	0.196	0.254	0.239	0.286	0.254	0.350
Additive Manufacturing	0.016	0.019	0.012	0.046	0.022	0.009	0.011	0.012	0.009	0.017
Simulation	0.023	0.022	0.018	0.059	0.087	0.036	0.102	0.018	0.036	0.045
Cybersecurity	0.031	0.022	0.024	0.059	0.065	0.012	0.034	0.024	0.012	0.032
Mobile Technologies	0.031	0.033	0.071	0.104	0.130	0.145	0.102	0.071	0.145	0.093
Adaptive Robotics	0.023	0.022	0.018	0.059	0.087	0.036	0.102	0.018	0.036	0.045

Accuracy	Cyber-Physical Systems	Cloud Computing	Internet of Things	Big Data and Analytics/ Artificial Intelligence	Additive Manufacturing	Simulation	Cybersecurity	Mobile Technologies	Adaptive Robotics	Relative importance
Cyber-Physical Systems	0.118	0.118	0.111	0.103	0.138	0.111	0.118	0.167	0.105	0.121
Cloud Computing	0.118	0.118	0.111	0.103	0.138	0.111	0.118	0.167	0.105	0.121
Internet of Things	0.118	0.118	0.111	0.103	0.138	0.111	0.118	0.083	0.105	0.112
Big Data and Analytics/ Artificial Intelligence	0.235	0.235	0.222	0.207	0.138	0.222	0.118	0.250	0.211	0.204
Additive Manufacturing	0.059	0.059	0.056	0.103	0.069	0.056	0.118	0.042	0.105	0.074
Simulation	0.118	0.118	0.111	0.103	0.138	0.111	0.118	0.083	0.105	0.112
Cybersecurity	0.059	0.059	0.056	0.103	0.034	0.056	0.059	0.042	0.053	0.058
Mobile Technologies	0.059	0.059	0.111	0.069	0.138	0.111	0.118	0.083	0.105	0.095
Adaptive Robotics	0.118	0.118	0.111	0.103	0.069	0.111	0.118	0.083	0.105	0.104

Context Awareness	Cyber-Physical Systems	Cloud Computing	Internet of Things	Big Data and Analytics/ Artificial Intelligence	Additive Manufacturing	Simulation	Cybersecurity	Mobile Technologies	Adaptive Robotics	Relative importance
Cyber-Physical Systems	0.290	0.204	0.385	0.316	0.191	0.210	0.154	0.275	0.242	0.252
Cloud Computing	0.058	0.041	0.048	0.035	0.128	0.017	0.128	0.028	0.027	0.057
Internet of Things	0.145	0.164	0.192	0.316	0.160	0.210	0.154	0.275	0.161	0.197
Big Data and Analytics/ Artificial Intelligence	0.097	0.123	0.064	0.105	0.160	0.210	0.128	0.138	0.161	0.132
Additive Manufacturing	0.048	0.010	0.038	0.021	0.032	0.026	0.077	0.028	0.027	0.034
Simulation	0.072	0.123	0.048	0.026	0.064	0.052	0.103	0.046	0.040	0.064
Cybersecurity	0.048	0.008	0.032	0.021	0.011	0.013	0.026	0.028	0.020	0.023
Mobile Technologies	0.145	0.204	0.096	0.105	0.160	0.157	0.128	0.138	0.242	0.153
Adaptive Robotics	0.097	0.123	0.096	0.053	0.096	0.105	0.103	0.046	0.081	0.089

Table 22Standardized comparison of the technologies cont.

Consistency index of the alternatives

Real-Time	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.219	2.178	9.948	0.118
Cloud Computing	0.113	1.131	9.995	0.124
Internet of Things	0.219	2.178	9.948	0.118
Big Data and Analytics/ Artificial Intelligence	0.107	1.078	10.098	0.137
Additive Manufacturing	0.024	0.234	9.587	0.073
Simulation	0.067	0.645	9.640	0.080
Cybersecurity	0.040	0.367	9.247	0.031
Mobile Technologies	0.147	1.440	9.780	0.098
Adaptive Robotics	0.064	0.614	9.611	0.076
			Consistency index average (CI)	0.095
			Consistency ratio (CR)	0.066
				Input data are consistent.
Adaptability and Dynamic	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.160	1.599	9.976	0.122
Cloud Computing	0.108	1.080	10.039	0.130
Internet of Things	0.179	1.803	10.076	0.135
Big Data and Analytics/ Artificial Intelligence	0.076	0.744	9.753	0.094
Additive Manufacturing	0.061	0.611	10.038	0.130
Simulation	0.103	1.091	10.544	0.193
Cybersecurity	0.021	0.203	9.517	0.065
Mobile Technologies	0.202	2.128	10.517	0.190
Adaptive Robotics	0.089	0.893	10.040	0.130
			Consistency index average (CI)	0.132
			Consistency ratio (CR)	0.091
				Input data are consistent.
Visibility and traceability	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index

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Cyber-Physical Systems	0.228	2.283	10.029	0.129
Cloud Computing	0.099	0.975	9.893	0.112
Internet of Things	0.214	2.122	9.914	0.114
Big Data and Analytics/ Artificial Intelligence	0.130	1.302	10.028	0.129
Additive Manufacturing	0.021	0.195	9.414	0.052
Simulation	0.070	0.694	9.988	0.123
Cybersecurity	0.051	0.471	9.267	0.033
Mobile Technologies	0.145	1.429	9.855	0.107
Adaptive Robotics	0.044	0.410	9.345	0.043
			Consistency index average (CI)	0.093
			Consistency ratio (CR)	0.064
				Input data are consistent.
Synchronization	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.246	2.557	10.390	0.174
Cloud Computing	0.052	0.487	9.291	0.036
Internet of Things	0.209	2.189	10.475	0.184
Big Data and Analytics/ Artificial Intelligence	0.166	1.776	10.703	0.213
Additive Manufacturing	0.043	0.410	9.471	0.059
Simulation	0.067	0.649	9.631	0.079
Cybersecurity	0.023	0.219	9.550	0.069
Mobile Technologies	0.113	1.144	10.142	0.143
Adaptive Robotics	0.080	0.771	9.613	0.077
			Consistency index average (CI)	0.115
			Consistency ratio (CR)	0.079
				Input data are consistent.
Autonomy	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.205	2.052	10.019	0.127
Cloud Computing	0.081	0.834	10.249	0.156
Internet of Things	0.205	2.052	10.019	0.127
Big Data and Analytics/ Artificial Intelligence	0.055	0.508	9.327	0.041

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Additive Manufacturing	0.100	0.984	9.881	0.110
Simulation	0.055	0.508	9.327	0.041
Cybersecurity	0.030	0.291	9.707	0.088
Mobile Technologies	0.134	1.417	10.581	0.198
Adaptive Robotics	0.137	1.388	10.153	0.144
			Consistency index average (CI)	0.115
			Consistency ratio (CR)	0.079
			Input data are consistent.	
Predictability	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.073	0.756	10.329	0.166
Cloud Computing	0.194	2.089	10.785	0.223
Internet of Things	0.099	0.989	9.962	0.120
Big Data and Analytics/ Artificial Intelligence	0.314	3.262	10.397	0.175
Additive Manufacturing	0.024	0.235	9.755	0.094
Simulation	0.075	0.752	10.063	0.133
Cybersecurity	0.037	0.346	9.289	0.036
Mobile Technologies	0.117	1.201	10.232	0.154
Adaptive Robotics	0.067	0.663	9.940	0.118
			Consistency index average (CI)	0.135
			Consistency ratio (CR)	0.093
			Input data are consistent.	
Integration and Interoperability of systems	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.214	2.146	10.044	0.131
Cloud Computing	0.066	0.641	9.751	0.094
Internet of Things	0.266	2.754	10.356	0.170
Big Data and Analytics/ Artificial Intelligence	0.112	1.151	10.263	0.158
Additive Manufacturing	0.018	0.171	9.598	0.075
Simulation	0.056	0.542	9.710	0.089
Cybersecurity	0.029	0.267	9.143	0.018
Mobile Technologies	0.164	1.719	10.506	0.188
Adaptive Robotics	0.076	0.755	9.930	0.116

			Consistency index average (CI)	0.115
			Consistency ratio (CR)	0.080
				Input data are consistent.
Scalability and Reconfiguration	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.166	1.732	10.440	0.180
Cloud Computing	0.039	0.359	9.272	0.034
Internet of Things	0.166	1.732	10.440	0.180
Big Data and Analytics/ Artificial Intelligence	0.038	0.351	9.316	0.039
Additive Manufacturing	0.343	3.697	10.790	0.224
Simulation	0.063	0.596	9.507	0.063
Cybersecurity	0.021	0.201	9.723	0.090
Mobile Technologies	0.078	0.773	9.898	0.112
Adaptive Robotics	0.088	0.877	10.002	0.125
			Consistency index average (CI)	0.116
			Consistency ratio (CR)	0.080
				Input data are consistent.
Distributed PPC	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.206	2.116	10.269	0.159
Cloud Computing	0.116	1.135	9.802	0.100
Internet of Things	0.111	1.065	9.584	0.073
Big Data and Analytics/ Artificial Intelligence	0.156	1.557	9.979	0.122
Additive Manufacturing	0.029	0.281	9.762	0.095
Simulation	0.027	0.255	9.595	0.074
Cybersecurity	0.082	0.795	9.697	0.087
Mobile Technologies	0.228	2.389	10.459	0.182
Adaptive Robotics	0.045	0.425	9.393	0.049
			Consistency index average (CI)	0.105
			Consistency ratio (CR)	0.072
				Input data are consistent.

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Collaboration and Cooperation	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.109	1.107	10.170	0.146
Cloud Computing	0.077	0.766	9.973	0.122
Internet of Things	0.143	1.526	10.679	0.210
Big Data and Analytics/ Artificial Intelligence	0.181	1.916	10.566	0.196
Additive Manufacturing	0.021	0.204	9.697	0.087
Simulation	0.037	0.357	9.538	0.067
Cybersecurity	0.094	0.970	10.285	0.161
Mobile Technologies	0.302	3.167	10.489	0.186
Adaptive Robotics	0.035	0.331	9.392	0.049
			Consistency index average (CI)	0.136
			Consistency ratio (CR)	0.094
				Input data are consistent.
Mass Customization	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.050	0.475	9.467	0.058
Cloud Computing	0.051	0.488	9.475	0.059
Internet of Things	0.170	1.904	11.213	0.277
Big Data and Analytics/ Artificial Intelligence	0.051	0.490	9.522	0.065
Additive Manufacturing	0.312	3.370	10.793	0.224
Simulation	0.090	0.898	9.945	0.118
Cybersecurity	0.020	0.202	9.967	0.121
Mobile Technologies	0.162	1.741	10.755	0.219
Adaptive Robotics	0.092	0.920	9.947	0.118
			Consistency index average (CI)	0.140
			Consistency ratio (CR)	0.097
				Input data are consistent.
Big data-driven	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.131	1.399	10.669	0.209

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Cloud Computing	0.196	2.115	10.787	0.223
Internet of Things	0.093	0.921	9.944	0.118
Big Data and Analytics/ Artificial Intelligence	0.350	3.859	11.040	0.255
Additive Manufacturing	0.017	0.170	9.819	0.102
Simulation	0.045	0.415	9.282	0.035
Cybersecurity	0.032	0.301	9.560	0.070
Mobile Technologies	0.093	0.921	9.944	0.118
Adaptive Robotics	0.045	0.415	9.282	0.035
			Consistency index average (CI)	0.130
			Consistency ratio (CR)	0.089
				Input data are consistent.
Accuracy	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.121	1.124	9.297	0.037
Cloud Computing	0.121	1.124	9.297	0.037
Internet of Things	0.112	1.030	9.219	0.027
Big Data and Analytics/ Artificial Intelligence	0.204	1.891	9.257	0.032
Additive Manufacturing	0.074	0.676	9.134	0.017
Simulation	0.112	1.030	9.219	0.027
Cybersecurity	0.058	0.529	9.157	0.020
Mobile Technologies	0.095	0.875	9.228	0.029
Adaptive Robotics	0.104	0.956	9.187	0.023
			Consistency index average (CI)	0.028
			Consistency ratio (CR)	0.019
				Input data are consistent.
Context Awareness	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.252	2.495	9.903	0.113
Cloud Computing	0.057	0.533	9.412	0.051
Internet of Things	0.197	1.992	10.090	0.136
Big Data and Analytics/ Artificial Intelligence	0.132	1.322	10.044	0.131
Additive Manufacturing	0.034	0.317	9.279	0.035

Simulation	0.064	0.634	9.938	0.117
Cybersecurity	0.023	0.216	9.388	0.048
Mobile Technologies	0.153	1.535	10.048	0.131
Adaptive Robotics	0.089	0.880	9.929	0.116
			Consistency index average (CI)	0.098
			Consistency ratio (CR)	0.067
			Input data are consistent.	

Table 23: Consistency index of the alternatives

AHP analysis using survey data

Criteria	Average Weight (A)	Product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Accuracy	0.076	0.965	12.746	0.068
Adaptability and Dynamic	0.130	1.591	12.284	0.026
Autonomy	0.036	0.454	12.467	0.042
Big data-driven	0.108	1.383	12.827	0.075
Context Awareness	0.042	0.529	12.681	0.062
Distributed PPC	0.061	0.766	12.485	0.044
Integration and Interoperability of systems	0.177	2.241	12.646	0.059
Mass Customization	0.055	0.688	12.554	0.050
Predictability	0.059	0.746	12.577	0.052
Real-Time	0.070	0.942	13.442	0.131
Synchronization	0.078	0.995	12.718	0.065
Visibility and traceability	0.108	1.383	12.827	0.075
			Consistency index average (CI)	**0.063**
			Consistency ratio (CR)	**0.041**

Table 24: Consistency test of the Criteria

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Accuracy	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	1	2	2	3	2	2	2	2	2
A2	1/2	1	1/2	1/2	1/2	1/2	1/2	1/2	1/2
A3	1/2	2	1	1	1	2	1	1	1
A4	1/3	2	1	1	1	2	1	1/2	1/2
A5	1/2	2	1	1	1	1	1	1	1
A6	1/2	2	1/2	1/2	1	1	1/2	1/2	1/2
A7	1/2	2	1	1	1	2	1	1	1
A8	1/2	2	1	2	1	2	1	1	1
A9	1/2	2	1	2	1	2	1	1	1

Big data-driven	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	1	7	4	4	7	9	7	6	5
A2	1/7	1	1/3	1/3	1/3	3	1/3	1/3	1/6
A3	1/4	3	1	1	4	6	4	1/3	1/4
A4	1/4	3	1	1	4	6	4	1/3	1/4
A5	1/7	3	1/4	1/4	1	4	1	1/4	1/6
A6	1/9	1/3	1/6	1/6	1/4	1	1/4	1/6	1/7
A7	1/7	3	1/4	1/4	1	4	1	1/4	1/6
A8	1/6	3	3	3	4	6	4	1	1/2
A9	1/5	6	4	4	6	7	6	2	1

Adaptability and Dynamic	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	1	5	1/3	1/2	1/4	3	1/3	1/3	1
A2	1/5	1	1/6	1/7	1/5	1/4	1/5	1/5	1/5
A3	3	6	1	1	2	5	2	1	2
A4	2	7	1	1	4	5	5	1	1
A5	4	5	1/2	1/4	1	1/2	1/3	1/2	1
A6	1/3	4	1/5	1/5	2	1	1/2	1/2	1/2
A7	3	5	1/2	1/5	3	2	1	1/2	1/2
A8	3	5	1	1	2	2	2	1	2
A9	1	5	1/2	1	1	2	2	1/2	1

Context Awareness	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	1	5	1/3	1	2	5	4	1/3	3
A2	1/5	1	1/6	1/5	1/4	1/3	1/4	1/6	1/5
A3	3	6	1	2	2	5	4	1/2	4
A4	1	5	1/2	1	3	5	3	1/2	5
A5	1/2	4	1/2	1/3	1	3	2	1/3	3
A6	1/5	3	1/5	1/5	1/3	1	1/2	1/6	1/4
A7	1/4	4	1/4	1/3	1/2	2	1	1/4	3
A8	3	6	2	2	3	6	4	1	5
A9	1/3	5	1/4	1/5	1/3	4	1/3	1/5	1

Autonomy	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	1	3	1/3	1/2	1/3	1/5	1	1/3	1/2
A2	1/3	1	1/5	1/5	1/3	1/2	1/3	1/5	1/4
A3	3	5	1	2	2	3	3	1	4
A4	2	5	1/2	1	1/2	4	2	1/2	3
A5	3	3	1/2	2	1	2	3	1/2	2
A6	5	2	1/3	1/4	1/2	1	5	1/3	1/2
A7	1	3	1/3	1/2	1/3	1/5	1	1/3	1/2
A8	3	5	1	2	2	3	3	1	4
A9	2	4	1/4	1/3	1/2	2	2	1/4	1

Distributed PPC	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	1	2	2	1/3	5	4	6	1	2
A2	1/2	1	1/2	1/2	3	4	2	1/2	1/2
A3	1/2	2	1	1/3	4	2	5	1	1/2
A4	3	2	3	1	4	6	6	1/2	5
A5	1/5	1/3	1/4	1/4	1	3	3	1/5	1/4
A6	1/4	1/4	1/2	1/6	1/3	1	1	1/6	1/5
A7	1/6	1/2	1/5	1/6	1/3	1	1	1/6	1/5
A8	1	2	1	2	5	6	6	1	4
A9	1/2	2	2	1/5	4	5	5	1/4	1

Table 25: Relative importance of the criteria

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Integration and Interoperability of systems	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	1	6	1/4	1/3	3	5	4	1/3	2
A2	1/6	1	1/7	1/5	1/4	4	1/4	1/7	1/5
A3	4	7	1	3	5	8	5	1	5
A4	3	5	1/3	1	4	8	3	1/2	4
A5	1/3	4	1/5	1/4	1	4	1	1/2	3
A6	1/5	1/4	1/8	1/8	1/4	1	1/4	1/9	1/5
A7	1/4	4	1/5	1/3	1	4	1	1/4	1/2
A8	3	7	1	2	2	9	4	1	4
A9	1/2	5	1/5	1/4	1/3	5	2	1/4	1

Real-Time	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	1	4	1/3	1/2	1	5	1	1/3	3
A2	1/4	1	1/4	1/4	1/3	3	1/3	1/4	1/3
A3	3	4	1	2	4	7	3	1	3
A4	2	4	1/2	1	4	5	4	1/2	1/2
A5	1	3	1/4	1/4	1	3	1	1/4	1/3
A6	1/5	1/3	1/7	1/5	1/3	1	1/2	1/7	1/4
A7	1	3	1/3	1/4	1	2	1	1/3	1/2
A8	3	4	1	2	4	7	3	1	3
A9	1/3	3	1/3	2	3	4	2	1/3	1

Mass Customization	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	1	5	1/3	1/4	1/3	1/5	1/2	1	1
A2	1/5	1	1/6	1/5	1/4	1/7	1/4	1/5	1/5
A3	3	6	1	3	4	1/4	3	3	2
A4	4	5	1/3	1	4	1/4	4	4	4
A5	3	4	1/4	1/4	1	1/5	1	3	4
A6	5	7	4	4	5	1	4	5	5
A7	2	4	1/3	1/4	1	1/4	1	3	4
A8	1	5	1/3	1/4	1/3	1/5	1/3	1	1
A9	1	5	1/2	1/4	1/4	1/5	1/4	1	1

Synchronization	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	1	5	1/2	4	3	5	3	1/2	3
A2	1/5	1	1/6	1/5	1/4	1/3	1/4	1/6	1/4
A3	2	6	1	4	3	5	4	1/2	4
A4	1/4	5	1/4	1	3	4	3	1/5	3
A5	1/3	4	1/3	1/3	1	3	1	1/3	3
A6	1/5	3	1/5	1/4	1/3	1	1/3	1/6	2
A7	1/3	4	1/4	1/3	1	3	1	1/3	1
A8	2	6	2	5	3	6	3	1	3
A9	1/3	4	1/4	1/3	1/3	1/2	1	1/3	1

Predictability	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	1	5	4	4	5	7	5	6	3
A2	1/5	1	1/4	1/4	1/3	3	1/3	1/3	1/4
A3	1/4	4	1	1	3	5	2	1/2	1/5
A4	1/4	4	1	1	4	4	3	1	1/2
A5	1/5	3	1/3	1/4	1	3	2	1	1/3
A6	1/7	1/3	1/5	1/4	1/3	1	1/4	1/3	1/5
A7	1/5	3	1/2	1/3	1/2	4	1	3	1/3
A8	1/6	3	2	1	1	3	1/3	1	1/5
A9	1/3	4	5	2	3	5	3	5	1

Visibility and traceability	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	1	4	1/3	2	3	6	2	1/2	1
A2	1/4	1	1/4	1/4	2	5	1/4	1/4	1/3
A3	3	4	1	1	4	6	5	1	3
A4	1/2	4	1	1	4	7	3	1/3	2
A5	1/3	1/2	1/4	1/4	1	4	1/2	1/4	1/3
A6	1/6	1/5	1/6	1/7	1/4	1	1/4	1/6	1/5
A7	1/2	4	1/5	1/3	2	4	1	1/5	1/2
A8	2	4	1	3	4	6	5	1	3
A9	1	3	1/3	1/2	3	5	2	1/3	1

Table 26: Relative importance of the criteria contd;

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Standardization of importance (Survey data analysis)

Accuracy	A1	A2	A3	A4	A5	A6	A7	A8	A9	Relative importance
A1	0.207	0.118	0.222	0.250	0.211	0.138	0.222	0.235	0.235	0.204
A2	0.103	0.059	0.056	0.042	0.053	0.034	0.056	0.059	0.059	0.058
A3	0.103	0.118	0.111	0.083	0.105	0.138	0.111	0.118	0.118	0.112
A4	0.069	0.118	0.111	0.083	0.105	0.138	0.111	0.059	0.059	0.095
A5	0.103	0.118	0.111	0.083	0.105	0.069	0.111	0.118	0.118	0.104
A6	0.103	0.118	0.056	0.042	0.105	0.069	0.056	0.059	0.059	0.074
A7	0.103	0.118	0.111	0.083	0.105	0.138	0.111	0.118	0.118	0.112
A8	0.103	0.118	0.111	0.167	0.105	0.138	0.111	0.118	0.118	0.121
A9	0.103	0.118	0.111	0.167	0.105	0.138	0.111	0.118	0.118	0.121
sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Adaptability and Dynamic	A1	A2	A3	A4	A5	A6	A7	A8	A9	Relative importance
A1	0.057	0.116	0.064	0.094	0.016	0.145	0.025	0.060	0.109	0.076
A2	0.011	0.023	0.032	0.027	0.013	0.012	0.015	0.036	0.022	0.021
A3	0.171	0.140	0.192	0.189	0.129	0.241	0.150	0.181	0.217	0.179
A4	0.114	0.163	0.192	0.189	0.259	0.241	0.374	0.181	0.109	0.202
A5	0.228	0.116	0.096	0.047	0.065	0.024	0.025	0.090	0.109	0.089
A6	0.019	0.093	0.038	0.038	0.129	0.048	0.037	0.090	0.054	0.061
A7	0.171	0.116	0.096	0.038	0.194	0.096	0.075	0.090	0.054	0.103
A8	0.171	0.116	0.192	0.189	0.129	0.096	0.150	0.181	0.217	0.160
A9	0.057	0.116	0.096	0.189	0.065	0.096	0.150	0.090	0.109	0.108
sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Autonomy	A1	A2	A3	A4	A5	A6	A7	A8	A9	Relative importance
A1	0.049	0.097	0.075	0.057	0.044	0.013	0.049	0.075	0.032	0.055
A2	0.016	0.032	0.045	0.023	0.044	0.031	0.016	0.045	0.016	0.030
A3	0.148	0.161	0.225	0.228	0.267	0.189	0.148	0.225	0.254	0.205
A4	0.098	0.161	0.112	0.114	0.067	0.252	0.098	0.112	0.190	0.134
A5	0.148	0.097	0.112	0.228	0.133	0.126	0.148	0.112	0.127	0.137
A6	0.246	0.065	0.075	0.028	0.067	0.063	0.246	0.075	0.032	0.100
A7	0.049	0.097	0.075	0.057	0.044	0.013	0.049	0.075	0.032	0.055
A8	0.148	0.161	0.225	0.228	0.267	0.189	0.148	0.225	0.254	0.205
A9	0.098	0.129	0.056	0.038	0.067	0.126	0.098	0.056	0.063	0.081
sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

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Big data-driven	A1	A2	A3	A4	A5	A6	A7	A8	A9	Relative importance
A1	0.416	0.239	0.286	0.286	0.254	0.196	0.254	0.563	0.654	0.350
A2	0.059	0.034	0.024	0.024	0.012	0.065	0.012	0.031	0.022	0.032
A3	0.104	0.102	0.071	0.071	0.145	0.130	0.145	0.031	0.033	0.093
A4	0.104	0.102	0.071	0.071	0.145	0.130	0.145	0.031	0.033	0.093
A5	0.059	0.102	0.018	0.018	0.036	0.087	0.036	0.023	0.022	0.045
A6	0.046	0.011	0.012	0.012	0.009	0.022	0.009	0.016	0.019	0.017
A7	0.059	0.102	0.018	0.018	0.036	0.087	0.036	0.023	0.022	0.045
A8	0.069	0.102	0.214	0.214	0.145	0.130	0.145	0.094	0.065	0.131
A9	0.083	0.205	0.286	0.286	0.218	0.152	0.218	0.188	0.131	0.196
sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Context Awareness	A1	A2	A3	A4	A5	A6	A7	A8	A9	Relative importance
A1	0.105	0.128	0.064	0.138	0.161	0.160	0.210	0.097	0.123	0.132
A2	0.021	0.026	0.032	0.028	0.020	0.011	0.013	0.048	0.008	0.023
A3	0.316	0.154	0.192	0.275	0.161	0.160	0.210	0.145	0.164	0.197
A4	0.105	0.128	0.096	0.138	0.242	0.160	0.157	0.145	0.204	0.153
A5	0.053	0.103	0.096	0.046	0.081	0.096	0.105	0.097	0.123	0.089
A6	0.021	0.077	0.038	0.028	0.027	0.032	0.026	0.048	0.010	0.034
A7	0.026	0.103	0.048	0.046	0.040	0.064	0.052	0.072	0.123	0.064
A8	0.316	0.154	0.385	0.275	0.242	0.191	0.210	0.290	0.204	0.252
A9	0.035	0.128	0.048	0.028	0.027	0.128	0.017	0.058	0.041	0.057
sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Distributed PPC	A1	A2	A3	A4	A5	A6	A7	A8	A9	Relative importance
A1	0.141	0.166	0.191	0.067	0.188	0.125	0.171	0.209	0.147	0.156
A2	0.070	0.083	0.048	0.101	0.113	0.125	0.057	0.105	0.037	0.082
A3	0.070	0.166	0.096	0.067	0.150	0.063	0.143	0.209	0.037	0.111
A4	0.422	0.166	0.287	0.202	0.150	0.188	0.171	0.105	0.366	0.228
A5	0.028	0.028	0.024	0.051	0.038	0.094	0.086	0.042	0.018	0.045
A6	0.035	0.021	0.048	0.034	0.013	0.031	0.029	0.035	0.015	0.029
A7	0.023	0.041	0.019	0.034	0.013	0.031	0.029	0.035	0.015	0.027
A8	0.141	0.166	0.096	0.404	0.188	0.188	0.171	0.209	0.293	0.206
A9	0.070	0.166	0.191	0.040	0.150	0.156	0.143	0.052	0.073	0.116
sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Integration and Interoperability of systems	A1	A2	A3	A4	A5	A6	A7	A8	A9	Relative importance

A1	0.080	0.153	0.072	0.044	0.178	0.104	0.195	0.082	0.101	0.112
A2	0.013	0.025	0.041	0.027	0.015	0.083	0.012	0.035	0.010	0.029
A3	0.321	0.178	0.290	0.400	0.297	0.167	0.244	0.245	0.251	0.266
A4	0.241	0.127	0.097	0.133	0.238	0.167	0.146	0.122	0.201	0.164
A5	0.027	0.102	0.058	0.033	0.059	0.083	0.049	0.122	0.151	0.076
A6	0.016	0.006	0.036	0.017	0.015	0.021	0.012	0.027	0.010	0.018
A7	0.020	0.102	0.058	0.044	0.059	0.083	0.049	0.061	0.025	0.056
A8	0.241	0.178	0.290	0.267	0.119	0.188	0.195	0.245	0.201	0.214
A9	0.040	0.127	0.058	0.033	0.020	0.104	0.098	0.061	0.050	0.066
sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Mass Customization	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**Relative importance**
A1	0.050	0.119	0.046	0.026	0.021	0.074	0.035	0.047	0.045	0.051
A2	0.010	0.024	0.023	0.021	0.015	0.053	0.017	0.009	0.009	0.020
A3	0.149	0.143	0.138	0.317	0.247	0.093	0.209	0.142	0.090	0.170
A4	0.198	0.119	0.046	0.106	0.247	0.093	0.279	0.189	0.180	0.162
A5	0.149	0.095	0.034	0.026	0.062	0.074	0.070	0.142	0.180	0.092
A6	0.248	0.167	0.552	0.423	0.309	0.371	0.279	0.236	0.225	0.312
A7	0.099	0.095	0.046	0.026	0.062	0.093	0.070	0.142	0.180	0.090
A8	0.050	0.119	0.046	0.026	0.021	0.074	0.023	0.047	0.045	0.050
A9	0.050	0.119	0.069	0.026	0.015	0.074	0.017	0.047	0.045	0.051
sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Predictability	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**Relative importance**
A1	0.365	0.183	0.280	0.397	0.275	0.200	0.296	0.330	0.499	0.314
A2	0.073	0.037	0.018	0.025	0.018	0.086	0.020	0.018	0.042	0.037
A3	0.091	0.146	0.070	0.099	0.165	0.143	0.118	0.028	0.033	0.099
A4	0.091	0.146	0.070	0.099	0.220	0.114	0.177	0.055	0.083	0.117
A5	0.073	0.110	0.023	0.025	0.055	0.086	0.118	0.055	0.055	0.067
A6	0.052	0.012	0.014	0.025	0.018	0.029	0.015	0.018	0.033	0.024
A7	0.073	0.110	0.035	0.033	0.028	0.114	0.059	0.165	0.055	0.075
A8	0.061	0.110	0.140	0.099	0.055	0.086	0.020	0.055	0.033	0.073
A9	0.122	0.146	0.350	0.198	0.165	0.143	0.177	0.275	0.166	0.194
sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Real-Time	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**Relative importance**
A1	0.085	0.152	0.080	0.059	0.054	0.135	0.063	0.080	0.252	0.107
A2	0.021	0.038	0.060	0.030	0.018	0.081	0.021	0.060	0.028	0.040
A3	0.255	0.152	0.241	0.237	0.214	0.189	0.189	0.241	0.252	0.219

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A4	0.170	0.152	0.121	0.118	0.214	0.135	0.253	0.121	0.042	0.147
A5	0.085	0.114	0.060	0.030	0.054	0.081	0.063	0.060	0.028	0.064
A6	0.017	0.013	0.034	0.024	0.018	0.027	0.032	0.034	0.021	0.024
A7	0.085	0.114	0.080	0.030	0.054	0.054	0.063	0.080	0.042	0.067
A8	0.255	0.152	0.241	0.237	0.214	0.189	0.189	0.241	0.252	0.219
A9	0.028	0.114	0.080	0.237	0.161	0.108	0.126	0.080	0.084	0.113
sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Synchronization	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**Relative importance**
A1	0.150	0.132	0.101	0.259	0.201	0.180	0.181	0.142	0.148	0.166
A2	0.030	0.026	0.034	0.013	0.017	0.012	0.015	0.047	0.012	0.023
A3	0.301	0.158	0.202	0.259	0.201	0.180	0.241	0.142	0.198	0.209
A4	0.038	0.132	0.051	0.065	0.201	0.144	0.181	0.057	0.148	0.113
A5	0.050	0.105	0.067	0.022	0.067	0.108	0.060	0.094	0.148	0.080
A6	0.030	0.079	0.040	0.016	0.022	0.036	0.020	0.047	0.099	0.043
A7	0.050	0.105	0.051	0.022	0.067	0.108	0.060	0.094	0.049	0.067
A8	0.301	0.158	0.404	0.324	0.201	0.216	0.181	0.283	0.148	0.246
A9	0.050	0.105	0.051	0.022	0.022	0.018	0.060	0.094	0.049	0.052
sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Visibility and traceability	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**Relative importance**
A1	0.114	0.162	0.074	0.236	0.129	0.136	0.105	0.124	0.088	0.130
A2	0.029	0.040	0.055	0.029	0.086	0.114	0.013	0.062	0.029	0.051
A3	0.343	0.162	0.221	0.118	0.172	0.136	0.263	0.248	0.264	0.214
A4	0.057	0.162	0.221	0.118	0.172	0.159	0.158	0.083	0.176	0.145
A5	0.038	0.020	0.055	0.029	0.043	0.091	0.026	0.062	0.029	0.044
A6	0.019	0.008	0.037	0.017	0.011	0.023	0.013	0.041	0.018	0.021
A7	0.057	0.162	0.044	0.039	0.086	0.091	0.053	0.050	0.044	0.070
A8	0.229	0.162	0.221	0.354	0.172	0.136	0.263	0.248	0.264	0.228
A9	0.114	0.121	0.074	0.059	0.129	0.114	0.105	0.083	0.088	0.099
sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 27: Standardization of importance

Alternatives Consistency index (Survey data)

Accuracy	**Average Weight (A)**	**product of Matrices (B)**	**Consistency Measure (B/A)**	**Consistency index**
Cyber-Physical Systems	0.204	1.891	9.257	0.032
Cloud Computing	0.058	0.529	9.157	0.020

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Internet of Things	0.112	1.030	9.219	0.027
Big Data and Analytics/ Artificial Intelligence	0.095	0.875	9.228	0.029
Additive Manufacturing	0.104	0.956	9.187	0.023
Simulation	0.074	0.676	9.134	0.017
Cybersecurity	0.112	1.030	9.219	0.027
Mobile Technologies	0.121	1.124	9.297	0.037
Adaptive Robotics	0.121	1.124	9.297	0.037
			Consistency index average (CI)	0.028
			Consistency ratio (CR)	0.019
data are consistent.				

Adaptability and Dynamic	**Average Weight (A)**	**product of Matrices (B)**	**Consistency Measure (B/A)**	**Consistency index**
Cyber-Physical Systems	0.076	0.744	9.753	0.094
Cloud Computing	0.021	0.203	9.517	0.065
Internet of Things	0.179	1.803	10.076	0.135
Big Data and Analytics/ Artificial Intelligence	0.202	2.128	10.517	0.190
Additive Manufacturing	0.089	0.893	10.040	0.130
Simulation	0.061	0.611	10.038	0.130
Cybersecurity	0.103	1.091	10.544	0.193
Mobile Technologies	0.160	1.599	9.976	0.122
Adaptive Robotics	0.108	1.080	10.039	0.130
			Consistency index average (CI)	0.132
			Consistency ratio (CR)	0.091

Autonomy	**Average Weight (A)**	**product of Matrices (B)**	**Consistency Measure (B/A)**	**Consistency index**
Cyber-Physical Systems	0.055	0.508	9.327	0.041
Cloud Computing	0.030	0.291	9.707	0.088
Internet of Things	0.205	2.052	10.019	0.127
Big Data and Analytics/ Artificial Intelligence	0.134	1.417	10.581	0.198
Additive Manufacturing	0.137	1.388	10.153	0.144
Simulation	0.100	0.984	9.881	0.110
Cybersecurity	0.055	0.508	9.327	0.041
Mobile Technologies	0.205	2.052	10.019	0.127
Adaptive Robotics	0.081	0.834	10.249	0.156

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Consistency index average (CI)	0.115
Consistency ratio (CR)	0.079
data are consistent.	

Big data-driven	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.350	3.859	11.040	0.255
Cloud Computing	0.032	0.301	9.560	0.070
Internet of Things	0.093	0.921	9.944	0.118
Big Data and Analytics/ Artificial Intelligence	0.093	0.921	9.944	0.118
Additive Manufacturing	0.045	0.415	9.282	0.035
Simulation	0.017	0.170	9.819	0.102
Cybersecurity	0.045	0.415	9.282	0.035
Mobile Technologies	0.131	1.399	10.669	0.209
Adaptive Robotics	0.196	2.115	10.787	0.223
Consistency index average (CI)				0.130
Consistency ratio (CR)				0.089
data are consistent.				

Context Awareness	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.132	1.322	10.044	0.131
Cloud Computing	0.023	0.216	9.388	0.048
Internet of Things	0.197	1.992	10.090	0.136
Big Data and Analytics/ Artificial Intelligence	0.153	1.535	10.048	0.131
Additive Manufacturing	0.089	0.880	9.929	0.116
Simulation	0.034	0.317	9.279	0.035
Cybersecurity	0.064	0.634	9.938	0.117
Mobile Technologies	0.252	2.495	9.903	0.113
Adaptive Robotics	0.057	0.533	9.412	0.051
Consistency index average (CI)				0.098
Consistency ratio (CR)				0.067
data are consistent.				

Distributed PPC	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.156	1.557	9.979	0.122

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Cloud Computing	0.082	0.795	9.697	0.087
Internet of Things	0.111	1.065	9.584	0.073
Big Data and Analytics/ Artificial Intelligence	0.228	2.389	10.459	0.182
Additive Manufacturing	0.045	0.425	9.393	0.049
Simulation	0.029	0.281	9.762	0.095
Cybersecurity	0.027	0.255	9.595	0.074
Mobile Technologies	0.206	2.116	10.269	0.159
Adaptive Robotics	0.116	1.135	9.802	0.100
			Consistency index average (CI)	0.105
			Consistency ratio (CR)	0.072
data are consistent.				

Integration and Interoperability of systems	**Average Weight (A)**	**product of Matrices (B)**	**Consistency Measure (B/A)**	**Consistency index**
Cyber-Physical Systems	0.112	1.151	10.263	0.158
Cloud Computing	0.029	0.267	9.143	0.018
Internet of Things	0.266	2.754	10.356	0.170
Big Data and Analytics/ Artificial Intelligence	0.164	1.719	10.506	0.188
Additive Manufacturing	0.076	0.755	9.930	0.116
Simulation	0.018	0.171	9.598	0.075
Cybersecurity	0.056	0.542	9.710	0.089
Mobile Technologies	0.214	2.146	10.044	0.131
Adaptive Robotics	0.066	0.641	9.751	0.094
			Consistency index average (CI)	0.115
			Consistency ratio (CR)	0.080
data are consistent.				

Mass Customization	**Average Weight (A)**	**product of Matrices (B)**	**Consistency Measure (B/A)**	**Consistency index**
Cyber-Physical Systems	0.051	0.490	9.522	0.065
Cloud Computing	0.020	0.202	9.967	0.121
Internet of Things	0.170	1.904	11.213	0.277
Big Data and Analytics/ Artificial Intelligence	0.162	1.741	10.755	0.219
Additive Manufacturing	0.092	0.920	9.947	0.118
Simulation	0.312	3.370	10.793	0.224
Cybersecurity	0.090	0.898	9.945	0.118
Mobile Technologies	0.050	0.475	9.467	0.058

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Adaptive Robotics	0.051	0.488	9.475	0.059
			Consistency index average (CI)	0.140
			Consistency ratio (CR)	0.097
data are consistent.				

Predictability	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.314	3.262	10.397	0.175
Cloud Computing	0.037	0.346	9.289	0.036
Internet of Things	0.099	0.989	9.962	0.120
Big Data and Analytics/ Artificial Intelligence	0.117	1.201	10.232	0.154
Additive Manufacturing	0.067	0.663	9.940	0.118
Simulation	0.024	0.235	9.755	0.094
Cybersecurity	0.075	0.752	10.063	0.133
Mobile Technologies	0.073	0.756	10.329	0.166
Adaptive Robotics	0.194	2.089	10.785	0.223
			Consistency index average (CI)	0.135
			Consistency ratio (CR)	0.093
data are consistent.				

Real-Time	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index
Cyber-Physical Systems	0.107	1.078	10.098	0.137
Cloud Computing	0.040	0.367	9.247	0.031
Internet of Things	0.219	2.178	9.948	0.118
Big Data and Analytics/ Artificial Intelligence	0.147	1.440	9.780	0.098
Additive Manufacturing	0.064	0.614	9.611	0.076
Simulation	0.024	0.234	9.587	0.073
Cybersecurity	0.067	0.645	9.640	0.080
Mobile Technologies	0.219	2.178	9.948	0.118
Adaptive Robotics	0.113	1.131	9.995	0.124
			Consistency index average (CI)	0.095
			Consistency ratio (CR)	0.066
data are consistent.				

Synchronization	Average Weight (A)	product of Matrices (B)	Consistency Measure (B/A)	Consistency index

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Cyber-Physical Systems	0.166	1.776	10.703	0.213
Cloud Computing	0.023	0.219	9.550	0.069
Internet of Things	0.209	2.189	10.475	0.184
Big Data and Analytics/ Artificial Intelligence	0.113	1.144	10.142	0.143
Additive Manufacturing	0.080	0.771	9.613	0.077
Simulation	0.043	0.410	9.471	0.059
Cybersecurity	0.067	0.649	9.631	0.079
Mobile Technologies	0.246	2.557	10.390	0.174
Adaptive Robotics	0.052	0.487	9.291	0.036
			Consistency index average (CI)	0.115
			Consistency ratio (CR)	0.079
data are consistent.				

Visibility and traceability	**Average Weight (A)**	**product of Matrices (B)**	**Consistency Measure (B/A)**	**Consistency index**
Cyber-Physical Systems	0.130	1.302	10.028	0.129
Cloud Computing	0.051	0.471	9.267	0.033
Internet of Things	0.214	2.122	9.914	0.114
Big Data and Analytics/ Artificial Intelligence	0.145	1.429	9.855	0.107
Additive Manufacturing	0.044	0.410	9.345	0.043
Simulation	0.021	0.195	9.414	0.052
Cybersecurity	0.070	0.694	9.988	0.123
Mobile Technologies	0.228	2.283	10.029	0.129
Adaptive Robotics	0.099	0.975	9.893	0.112
			Consistency index average (CI)	0.093
			Consistency ratio (CR)	0.064
data are consistent.				

Table 28: Alternatives consistency index (Survey data)

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Appendix B

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