The smart SME technology readiness assessment methodology in the context of industry 4.0

SAAD, Sameh M <http://orcid.org/0000-0002-9019-9636>, BAHADORI, Ramin <http://orcid.org/0000-0001-6439-7033> and JAFARNEJAD, Hamidreza

Emerald Journal of Manufacturing Technology Management

The Smart SME Technology Readiness Assessment Methodology in the Context of Industry 4.0

Journal:	*Journal of Manufacturing Technology Management*
Manuscript ID	JMTM-07-2020-0267.R2
Manuscript Type:	Article
Keywords:	Industry 4.0, Product design, Small and Medium Sized Enterprises

The Smart SME Technology Readiness Assessment Methodology in the Context of Industry 4.0

Abstract

Purpose – This study proposes the Smart SME Technology Readiness Assessment (SSTRA) methodology which aims to enable practitioners to assess the SMEs Industry 4.0 technology readiness throughout the end-to-end engineering across the entire value chain; the smart product design phase is the focus in this paper.

Study design/methodology/approach – The proposed SSTRA utilises the analytic hierarchy process to prioritise smart SME requirements, a graphical interface which tracks technologies' benchmarks under Industry 4.0 Technology Readiness Levels (TRLs); a mathematical model used to determine the technology readiness and visual representation to understand the relative readiness of each smart main area. The validity of the SSTRA is confirmed by testing it in a real industrial environment. In addition, the conceptual model for Smart product design development is proposed and validated.

Findings – The proposed SSTRA offers decision-makers the facility to identify requirements and rank them to reflect the current priorities of the enterprise. It allows SMEs to assess their current capabilities in a range of technologies of high relevance to the Industry 4.0 area. The SSTRA assembles a readiness profile allowing decision-makers to not only perceive the overall score of technology readiness but also the distribution of technology readiness across the main smart areas. It helps to visualise strengths and weaknesses; whilst emphasising the fundamental gaps that require serious action to assist the program with a well-balanced effort towards a successful transition to Industry 4.0.

Originality/value – The SSTRA provides a step-by-step approach for decision-making based on data collection, analysis, visualisation, and documentation. Hence, it greatly mitigates the risk of further Industry 4.0 technology investment and implementation.

Keywords: Industry 4.0, Smart Product Design, Maturity Model, SMEs, Assessment methodology

1. Introduction

In today's competitive market in order to address the increased complexity of products and supply chain, the urgency of more responsive production systems and processes is undeniable. Hence, by addressing recent technological developments and due to an increase in customer's demands for customised products with high quality and lower costs; the emergence of a new industry model has been stressed under the topic of Industry 4.0 (Hermann, 2016). Industry 4.0 is the newest industrial revolution that was announced in Hannover in 2011 to describe the trend of interconnectivity and digitalisation in manufacturing that is embodied in cyber-physical systems (Fareri *et al*., 2020). It highlights the importance of new and innovative technologies being readily available to businesses in the 21st Century. The three previous 'industrial revolutions' that preceded the concept of Industry 4.0, all relate to the introduction of engine power, mass production with the aid of electrical power and automation using IT and electronics (Mogos *et al*., 2019). Industry 4.0 represents the next step to significantly increase the efficiency and quality of the products; whilst offering flexibility and customisation which is not possible with conventional production systems. It promises to offer huge opportunities for companies regarding modular, efficient, and intelligent systems using software to improve performance by analysing data (Lee *et al*., 2015). This allows the creation of customised products in a batch size of one with the same economic conditions as mass producing them. According to Lee *et al*. (2013), a production system with these capabilities will significantly increase the economic potential of countries. Industry 4.0, like many of the previous industrial revolutions, is wide open to a large array of sectors that could be impacted by its advanced technology. Any business that relies on data to make decisions, can and will be affected by Industry 4.0.

Nowadays, Small and Medium-Sized Enterprises (SMEs) are the backbone of every industry and economy around the world. According to the European Commission (2012), SMEs might be characterised as the businesses with a staff headcount of less than 250 and turnover of no more than EUR 50 million, and/or an annual balance sheet total not exceeding EUR 43 million. The growth and prosperity of every society is guaranteed by SMEs (Anderl *et al*., 2015). They act as the driving force of many manufacturing economies (Mittal *et al*., 2018) and are widely known as capable innovators due to their "flat organisational structure" and are more "flexible" in comparison with Multi-National Enterprises (MNEs). Thus, SMEs must be developed in terms of technology to optimise their performance by integrating and applying the concept of Industry 4.0 to be able to compete nationally and internationally. To better understand the technology requirements for an SME to become Industry 4.0 recognised; the nine pillars of Industry 4.0 are employed to highlight the areas in which an SME can implement new technologies; thereby becoming integrated, autonomous, and optimised (Vaidya *et al.*, 2018). Table I provides the most important points of these main aspects and summarises the goal of each technology.

[**Table I** *near here*]

But SMEs in comparison with MNEs face various challenges in transforming to Industry 4.0 due to limitations on internal resources, specialist workforce, and the lack of knowledge and experience when defining the appropriate strategy which elevates Industry 4.0 from theory to practice (Löfving *et al.*, 2014; Rondini *et al.*, 2018; Torn and Vaneker, 2019). Moreover, SMEs do not have a certain perspective about "the financial effort" required for the acquisition of such new technology nor on the overall impact on their business model (Schumacher *et al.*, 2016). Although many SMEs have recognised the opportunities offered by Industry 4.0, many of them are still reluctant to introduce solutions (Schumacher *et al.*, 2016). Therefore, to overcome "growing uncertainty and dissatisfaction" in manufacturing companies, regarding the idea of Industry 4.0, new methods and tools are needed to provide guidance and support to align business strategies and operations (Schumacher *et al.*, 2016; Pirola *et al.*, 2019). While, the problems regarding implementing Industry 4.0 in SMEs are clear in the literature; still, the questions remain regarding how to measure the extent to which an enterprise is ready to implement Industry 4.0, or how much a company is developed with respect to Industry 4.0, or how to benchmark SMEs with respect to the Industry 4.0 readiness level. Therefore, the need for readiness models to provide tools for assessing the company's current readiness to implement Industry 4.0's aspects and to identify specific actions to help them reach a higher readiness level to maximise benefits are widely considered. Thus, the main objective of this research work is to introduce an assessment method to provide a systematic approach which enables SMEs in order to examine their current level of technology readiness toward Industry 4.0 throughout the end-to-end engineering across the entire value chain focusing on the smart product design phase. The remainder of the paper is organised as follows: in the next section, the research background is provided. In section 3, the hierarchical requirements model for Smart product design development is proposed. Later, in section 4, a detailed explanation of SSTRA methodology is outlined. The validation of the proposed hierarchical requirements model is presented in section 5. Section 6 covers the application of the SSTRA in a real industrial case. Then, the paper ends with overall conclusions and future work.

2. Research Background

According to Schumacher *et al.* (2016), the term "maturity" refers to a "state of being complete, perfect, or ready" and indicates progress in the development of a system. A maturity model may be referring to a conceptual structure, consisting of sections that define maturity or development status, from a designated study area (Santos and Martinho, 2019). Maturity models provide extensive knowledge of the current state of companies and a way to pursue the implementation of Industry 4.0 strategies (Akdil *et al*., 2018). These models are frequently used as a tool to conceptualise and measure an enterprise's maturity or a process about a specific target situation (Schumacher *et al*., 2016). "Maturity models" and "readiness models" are often used synonymously, but there is little difference in their definitions. Readiness models act as the assessment tools to make it clear whether the organisation is ready to begin the development process or not. However, maturity models aim to indicate what level of maturity the organisation is at and provide step-by-step guidance for the continuous improvement process (Mittal *et al*., 2018). To obtain proper models regarding SME requirements; the following paragraphs aim to review the most current adapted maturity models, developed to help companies measure their readiness in their transformation to Industry 4.0.

IMPULS is one of the popular models proposed by Lichtblau *et al.* (2015) which provide an online auto-check tool that allows companies to know in which areas they are well prepared for Industry 4.0 and in which they still need more improvement. The IMPULS assessment includes six dimensions (i.e. organisational strategy, smart factory, smart operation, smart products, data-driven services, and employees) along with eighteen sub-dimensions to classify company readiness within the six levels of readiness model as an outsider, newcomer, intermediate, experienced, expert and finally top performer. This model is timesaving, and the resources involved are based on an online tool. In addition, there is no need for a high level of digitalisation knowledge from people who want to fill out the form. However, it seems the selected dimensions are not well defined for SMEs as they would rarely be able to achieve a good score in these dimensions and, as a result, most of the SMEs may be categorised at the lowest level of Industry 4.0 (i.e. outsiders). Schumacher *et al*. (2016) developed a maturity model to determine the readiness level of an SME to implement Industry 4.0 technologies, digital and intelligent automation methods. This model has three separate steps including an initial step to create a comprehensive understanding of the field of industry 4.0, the main development step for designing the structure of the model and an implementation step for validating the tool results in the real-life program. The model consists of nine dimensions (i.e. strategy, leadership, customers, products, etc.) and sixty-two evaluation items for five levels of the maturity model. In this maturity model, assessment questionnaire is utilised based on a five-point Likert scale for each question. This model has a good level of transparency and is very easy to understand. Some background knowledge is essential at the initial step, as this is the basis for determining assessment weights. However, not all of sixty-two evaluation items are presented and discussed within the paper. It seems this model due to its main technical and executive requirements can be suitable for SMEs. Another "connected enterprise maturity model" has been developed by Rockwell Automation (2014) in which technology is the key enabler. In this model, five stages are proposed to examine the existing operation technology and information technology networks (stage 1), protecting and upgrading the networks and control units from the factory floor up to selling networks (stage 2), defining, creating, organising and developing a working data capital to collect information (stage 3), data analytics including real-time analytics, proactive and automatic analytics (stage 4) and enhancing collaboration between enterprise and environment (stage 5). They also suggested four different technological dimensions required to achieve Industry 4.0; including (1) Information infrastructure consists of hardware and software, (2) Data exchange and controls devices such as sensors, actuators, motor controls, switches, etc., (3) Networks which act as a platform for exchanging all information, and (4) Data security strategies. Since not many details about the structure, maturity items and assessment tool are provided (white paper); the judgment about its applicability to SMEs is limited. Akdil *et al*. (2018) presented an Industry 4.0 maturity model with four levels of maturity (i.e. absence, existence, survived, and maturity) and three dimensions including "smart products and services", "smart business processes", and "strategy and organisation". The assessment questionnaire is provided and deployed in a retail company operating to help the company identify its status in relation to Industry 4.0. Although indications of progress towards Industry 4.0 are not provided, the level of importance of items and dimensions is not considered, and the SME perspective is not intended for Industry 4.0. Ganzarain and Errasti (2016) developed the maturity model for SMEs transition to Industry 4.0 with three stages (i.e. Envision, Enable, and Enact) along with five steps including Initial, Managed, Defined, Transform and Detailed Business. This model is focused on company cultural, skills and technology. Since this method is based on self-assessment, it may not be easy for SMEs to implement this model due to a lack of experience and expertise. Jung *et al.* (2016) assessed smart manufacturing readiness in SMEs under four dimensions: organisational maturity, information technology maturity, performance management maturity and information connectivity maturity. However, statistical analysis is performed to validate the model, the steps to reach Industry 4.0 are not considered, hence, its applicability to SMEs is vague.

A summary of the literature review is given in Table II. There are a few Industry 4.0 technology readiness tools/methodologies that have been developed to help SMEs in their transition to Industry 4.0. Specifically, by examining the developed maturity and readiness models that are available in the literature, this lack is more evident throughout the end-to-end engineering across the entire value chain.

[**Table II** *near here*]

3. The hierarchical requirements model for Smart product design development

With the beginning of Industry 4.0 and the increasing efforts to realise a smart industrial environment, product design must also undergo a fundamental change. It is worth noting that unlike production, which Industry 4.0 allows a shift of the work away from human intervention, product design requires the integration of information and people at different levels and in various forms (Rauch *et al.*, 2016). This is taken into account, in this research, as shown in figure 1; by a careful examination of the literature and expert's opinion in this area; the hierarchical requirements model for smart product design development is proposed. The proposed model consists of three main criteria for smart product design development, namely: Design Execution, Design System Flexibility and Design Real-Time Data Management. Each main criterion comprises three drivers, and each driver has two technologies. Later, this model is contributed as a benchmark in this field to the industrial application of the SSTRA methodology while it could be modified based on the nature of SME during the requirement capture workshops (see Section 6). In the following sub-sections, a detailed explanation of the proposed model is provided.

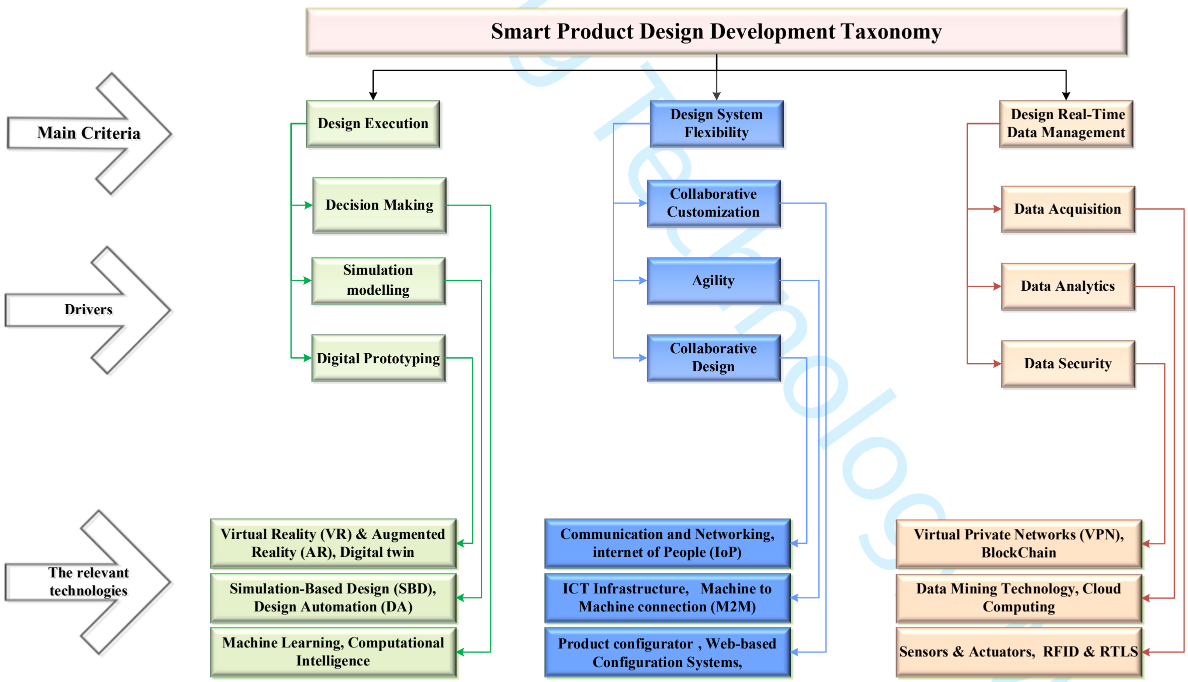

Figure 1. The hierarchical requirement model for smart product design development

3.1. Design Real-Time Data Management

A real-time design system is a "database system" which uses "real-time data processing" to handle workloads whose state is constantly changing. It provides a cross-sharing of product design information and the visualisation of design changes in real-time which is crucial to find out the status of the product (Lau *et al.*, 2003; Canedo, 2016). As part of design real-time data management system, the use of data acquisition is essential to collect different streams of information in real-time from related databases such as the product, customers, etc. (Schlechtendahl, 2015). In this regard, Radio Frequency Identification (RFID) and Real-Time Locating Systems (RTLS) are considered the most advanced technologies to capture real-time data across the entire product life cycle (Brusey and McFarlane, 2009; Arica and Powell, 2014). For instance, the permanent integrated RFID and RTLS tags can provide a real-time connection the so-called "real-time bidirectional coordination" between the design team and shop floor which support and meet customer's ever-changing requirements more effectively (Akanmu *et al*., 2012). Also, Sensors and Actuators are low-level devices that are directly responsible for communicating with the physical world; whether this is to measure some variables and transfer them to a higher level or enabling higher-level devices to affect the real world (Iglesias-Urkia *et al*., 2017). The textile and fashion industry is a good example in which, by embedding sensors in clothes, companies would then be able to collect environmental data and exchange it with the database in real-time. Moreover, these clothes may be able to provide the right services depending on the changing conditions. For instance, they may sense some changes in wearer's health condition by collecting some variables like biomedical signals and body temperature and inform the wearer through the built-in actuators (Jeong and Yoo, 2009). This valuable information would help designers to learn more about the working condition of the clothes and provide customers with the best possible designs. A design real-time data management system also focuses on the management and optimisation of design processes through monitoring and data analytics in which information is analysed and processed in real-time to use in new product designs and development stages (Wang *et al*., 2016; Konstantinov *et al*., 2017). The dynamic customer's requirements have been getting more complicated, especially in today's competitive market, which has made product design a very complicated task. This is where Data Mining technology empowers SMEs to extract and analyse hidden predictive information from among the large and complex generated data in order to recognise valuable customers, providing an accurate prediction of the future market and more efficiency in product innovation. Altogether, it will grant SMEs with the "knowledge-driven decisions" the capacity to create better designs (Huang and Chang, 2005). Cloud Computing can also be utilised to meet both the computational and data storage requirements from big data analytics applications. By facilitating the integration among the data, design tools and simulations through the distributed and collaborative setting (Wu *et al*., 2014), Cloud Computing grants a fast, flexible, and most importantly, low-cost design system that can be shared among several parties. Due to widespread use of Cloud Computing in designed real-time data management systems, the need for data security is critical to enhancing security in "Data Transfer", "Data Storage" and "Data Lineage" (Manogaran *et al*., 2017). Block-chain is one of the technologies that can add trust, security, and decentralisation to a variety of industries including SMEs (Morabito, 2017). A virtual private network (VPN) would also extend security for data shared over the public network to and including company applications (Aldridge *et al*., 2011).

3.2. Design System Flexibility

A flexible design system is a system in which all main internal and external stakeholders (e.g. customers, company staff and CEO) participate in the design and development phase of a product. By addressing the goal of Industry 4.0, this system is also very agile and can respond quickly to environment changes (Jazdi, 2014). The flexibility of a design system can be measured by its speed in feeding the production line (Zawadzki and Żywicki, 2016). The smart product design system will be able to achieve maximum flexibility through the highest possible Collaborative Customisation. It means understanding and following customers' requirements and wishes in the design and development stage. In other words, the extent to which customers can customise the product they want? (Dou *et al*., 2016). This collaborative customisation can be supported by employing some advanced technologies such as web-based and software-based (virtual concept test) configurators. Configurators would make SMEs able to provide customers with the opportunity for real-world interaction experience in the virtual environment with the product (Grosso *et al*., 2014). The very first benefit of this close interaction is understanding and learning the needs of customers from the design team directly. Agility is also one of the main drivers of a flexible design system. It refers to how agile the system is and how quick in responding to market changes, customers' requirements and wishes as well as implementing ideas from different parts of the company (Rebentisch *et al*., 2018). The technologies which equip SMEs with agile systems are ICT infrastructure and Machine-to-Machine Connections (M2M). A well-defined and organised ICT infrastructure will increase the speed of product development decision-making in SMEs, which will grow their competitive level and make them able to compete with larger companies in their industry field (Dickerhof, 2010). Santos *et al*. (2017) defined M2M as the automatic information exchange among cyber-physical systems (CPSs); which is one of the main columns of Industry 4.0, which provides SMEs with a more "sophisticated, dynamic and content-rich" design system enriched by the real-time data stream. The last of a flexible design system is the Collaborative Design which refers to the extent to which a company's stakeholders can participate in the design and product development phase (Yin and Qin, 2019). Technologies that make the Collaborative Design possible for SMEs are Collaborative Network and the Internet of People (IoP). Torn and Vaneker (2019) defined the former as a cross-linking network to facilitate exchange data across all levels of SMEs, which will increase the flexibility and quality of new product development by making sure that all stakeholders expectations are considered. Also, by employing the IoP, SMEs would be able to consider the stakeholders' (e.g. staff, CEO etc.) "context", which will enable them to learn and collect suitable information for the smart design system (Miranda *et al*., 2015).

3.3. Design Execution

Design Execution refers to the stage in which the product is started to design and develop regarding the data and information which has been collected and analysed (Hermann, 2016). Decision Making is one of the main drivers of Design Execution. A good product cannot be designed and developed by accident (Zawadzki and Żywicki, 2016). Therefore, the design process should be a solid and rational step-by-step process, which starts with making a decision. Decision-making refers to the cognitive process that leads to timely decisions for a design specification based on the customers' preferences and wishes among available alternatives (Hajji *et al*., 2011). SMEs who wish to be able to take the maximum benefits from Industry 4.0 in the decision-making stage, need to employ some advanced technologies such as Machine Learning (ML) and Computational Intelligence (CI). Romeo *et al*. (2011) noted that fewer man-hours, company's knowledge protection, and more accurate and faster decision-making processes are some of the main advantages of using ML technology with SMEs in product design decision making. CI refers to the ability of a computer to learn to design from data or experimental observation. In other words, machines start thinking and predicting better design based on the available data in the database system (Siddique and Adeli, 2013). The second driver is Simulation Modelling. It is a way to construct physical, mathematical, or other types of models of a system or a process to be able to understand and predict its behaviour more efficiently (Rodič, 2017). Simulation-Based Design (SBD) and Design Automation (DA) are two technologies which help SMEs towards Industry 4.0 in the Simulation Modelling area. SBD is defined as a process in which simulation plays a significant role in design evaluation and verification. It is used to understand and predict the behaviour of the product and enable companies to identify any changes needed to help superior design products in the least time and at the right costs (Shephard *et al*., 2004). DA refers to a set of software tools for designing systems that all tasks through the design process including designing, building, testing, and analysing are executed together with target behaviour (Appleton *et al*., 2017). It is a learning-by-doing process which represents, evaluates and visualises different variations. The final driver of the Design Execution criterion is Digital Prototyping; it means to use product data models rather than physical prototypes for product design analysis and evaluations (Dai *et al*., 1995). Brettel *et al*. (2014) defined prototyping as making an early sample, model, or release of a product built to test a concept or process. Virtual Reality (VR), Augmented Reality (AR) and Digital Twin are the main technologies which can be employed by SMEs towards implementing Industry 4.0 principles. According to Salkin *et al*. (2018), VR and AR can provide SMEs with the great opportunity by testing and examining different what-if scenarios. These technologies would make SMEs able to detect the problems and improve the product design continually. Uhlemann *et al*. (2017) cited Digital Twin as another technology which is vital for releasing the maximum potential of Industry 4.0 by SMEs. They argued a Digital Twin is “a digital replica of a product” which is connected to the real product through a real-time connection. The Digital Twin technology can help SMEs to have a comprehensive view of the product life cycle by observing the behaviour of the digital twin under different working situations which will eventually lead them to design and develop better products (Bal and Satoglu, 2018).

4. Proposed SSTRA methodology

SSTRA is an integrated framework based on closely coupling several techniques and methodologies to enabling SMEs to examine their level of technology readiness to implement Industry 4.0. The concept of the SSTRA methodology came from a research work about Industry 4.0 transition readiness throughout the end-to-end engineering across the entire value chain, which was conducted at Sheffield Hallam University (SHU) by the Integrated Manufacturing & Supply Chain Management Research Group. The main targets of the SSTRA are SMEs stakeholders and, more specifically, their decision-makers who play a vital role in SMEs transition to Industry 4.0. There are also other audiences such as city councils, local or national governments and third-party consultant firms who can use the SSTRA method to help local SMEs in their transition to Industry 4.0. In comparison with available readiness/maturity models, SSTRA provides a systematic approach which allows practitioners to measure technology capability/readiness in SMEs throughout the end-to-end engineering across the entire value chain for implementing Industry 4.0. In other words, the SSTRA has been created to help SMEs to evaluate their current situation with respect to Industry 4.0 requirements so to identify what technologies need to be implemented effectively in order to address the SME operation requirement. Moreover, it helps them to have a clear perspective about their strengths and weaknesses which means they would be able to decide in which areas or technologies they need to focus more to keep their products and operation compatible in a competitive market. Hence, it highly reduces the investment and implementation risks for the company. The SSTRA also gives this opportunity to the SMEs to identify key barriers in their transition to Industry 4.0., It represents an advance in the state-of-the-art of SMEs readiness assessment methods in that it offers a step-by-step approach to decision-making based on data collection, analysis, visualisation, and documentation. It does this to support SMEs gain the benefits of Industry 4.0. Implementation of the SSTRA process consists of three main phases, including Requirements data collection phase, Technology benchmarking phase and Assessment phase, as explained in the following sections. Figure 2 shows the SSTRA framework with its three phases and illustrates the flow of activity from beginning to end.

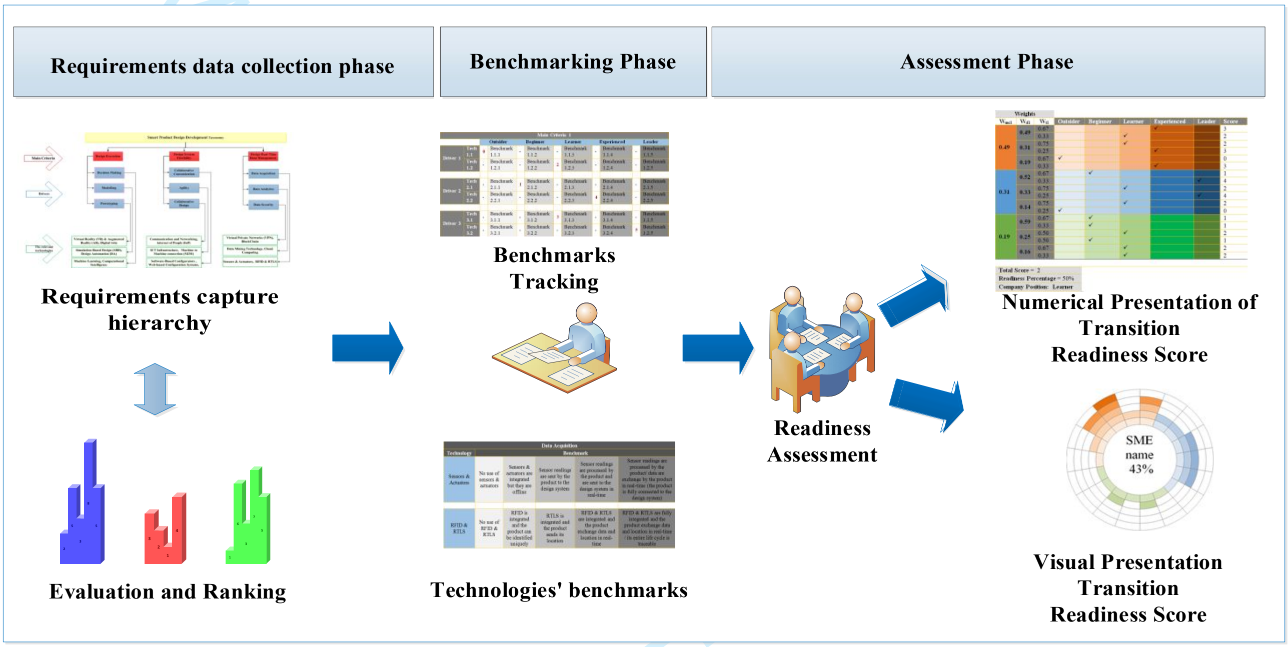

Figure 2. SSTRA Overall Framework

4.1. Requirements data collection phase

The SSTRA has been shaped to help assessors to collect available information and data to analyse an SME readiness for implementing Industry 4.0 in their enterprise. Thus, the data collection phase is started by mapping the detailed descriptions and classifications (taxonomy) of the technologies of relevance to SME operation via facilitated workshops. This allows SME to identify, select, and prioritise technologies to satisfy the market and product needs, enterprise drivers and technology competitiveness position to process it in a standardised manner; in order to analyse an SME readiness for implementing Industry 4.0 in their enterprise.

Evaluation and ranking the key elements (e.g. technologies) that are essential for enterprise transition success is the main objective of the requirements data collection phase. SMEs should have an opportunity to determine their relative importance of each main criteria, drivers and technologies which can be decided directly by assigning weight (W) to each criterion. The SMEs are very limited from the resources point of view, so they may need to know where to invest; which technology, driver or criterion would help them more toward achieving Industry 4.0 readiness. This ranking activity is carried out via facilitated workshops, utilising an Analytic Hierarchy Process (AHP) tool.

Since consensus is crucial at this stage, the AHP can offer transparency in the process and build consensus and confidence through ranking the relative importance of key factors (Gindy *et al.*, 2008). The output of this phase later contributes to the assessment of transition readiness through the assessment phase.

4.2. Technology benchmarking phase

The technology benchmarking phase of the SSTRA process is carried out using a graphical interface enabling the SME to make an accurate assessment of its technology readiness position regarding five Technology Readiness Levels (TRLs). Each technology has five benchmarks (*Si*), the value starts from (0-4), corresponding to the TRLs: *Outsider*, *Beginner*, *Learner*, *Experienced* and *Leader* that must be met to complete the level. This allows SMEs to easily compare their readiness to identify their current situation concerning a specific technology.

For instance, Table III provides the detail of the proposed technologies' benchmarks (*Si*) that are under the Data Acquisition driver in figure 1. Each technology (e.g. Sensors & Actuators) is assessed using one of five available benchmarks to indicate progress towards a successful transition to Industry 4.0, which are:

- ***Si*=0 is *Outsider***: Generally, the *outsider* refers to SMEs who follow the conventional methods and technologies to develop and design a product. They are not aware and confident enough to start their journey towards Industry 4.0 or they might assume that Industry 4.0 is irrelevant to them. For instance, from sensors & actuators technology point of view, the products are developed and designed just based on human judgment without receiving any direct and first-hand data from sensors and actuators embedded in the product. In other words, for designing a product, the company is relying on design team experience and second-hand or indirect data.
- ***Si*=1 is *Beginner***: A *beginner* company refers to a company who has started to think about changing its strategy to employ Industry 4.0 technologies to design and develop a smart product. It shows an enthusiasm to implement Industry 4.0. Additionally, a few technologies related to Industry 4.0 are adapted to the design department, but investment in this area is very limited. In regard to sensors & actuators, these companies use offline sensors and manual actuators to collect data and adjust product regarding new working conditions. The offline sensors collect and store data, and data is periodically transferred to the company and the design team. This can be used for monitoring and diagnosing to prevent damages and collect useful data which help designers to develop better products (Akbari *et al.*, 2004).
- ***Si*=2 is *Learner***: The *learner* refers to a company who defined a clear roadmap towards implementing Industry 4.0 technologies and started using some Industry 4.0 technologies, but to

a limited extent. In connection with sensors & actuators, these companies use online sensors which are responsible for collecting data and sending it to the design team. The product does not process data and just sends raw data. Moreover, the manual actuators are implemented in the product to update it regarding the product's working condition. An example of online sensors can be found in Bosch GmbH products. Sensors are integrated into the Bosch transport packaging and continuously collect product quality data such as temperature, humidity, and shock during its life cycle (Uhlemann *et al.*, 2017). These sensors are connected to the Bosch IoT cloud system and help the company's design and development team to develop better products.

- ***Si*=3 is *Experienced***: It refers to a company who employed Industry 4.0 technologies and strategies to a good extent, but it needs to invest more resources in this area to realise the ultimate potential of Industry 4.0. The company uses Industry 4.0 technologies to a very good extent to design and develop new products or redesign the existing products. For example, as shown in table III, regarding sensors & actuators, these companies employ integrated online sensors which have a data processing unit. These sensors analyse data and send the most appropriate data through a seamless flow of data. The advanced pneumatic valves from AVENTICS GmbH are appropriate examples of such level of integration. These valves are equipped with smart sensors which can measure and process data which makes them able to provide useful information and documentation for spare parts and system documentation in the design phase according to the company's claim (AVENTICS, 2017). Moreover, this data is used for designing new products and redesigning the existing ones.
- ***Si*=4 is *Leader***: Finally, a *leader* refers to an SME which entirely employed Industry 4.0 related technologies and strategies to design and develop a product or redesign and improve the existing products. In other words, they satisfy all technology requirements for smart product design, this is the highest readiness level. For example, these companies fully integrated the smart sensors empowered with a processing unit and smart actuators which adjust and correct the product situation wherever it is needed. These integrated smart sensors and actuators enrich the design team with first-hand, direct access, appropriate and most importantly, real-time seamless data flow (Jazdi, 2014). One example, near future clothing named "the very smart textile" (Jeong and Yoo, 2009) will be able to collect environmental data by sensors and exchange it with the database in real-time which is discussed in section 4.1.

The rest of the related Industry 4.0 technologies' benchmarks under each driver is provided in detail in appendix 1, Tables A1-A8. The benchmarking step provides an input to the assessment phase to measure the transition readiness.

[**Table III** *near here*]

4.3. Assessment phase

To quantify progress, the assessors benefit the information gained from prior phases to evaluate the SME transition readiness. In this phase, the SME is assessed based on the appropriate weighting (W_{ti}, W_{dj}, and W_{mcz}) given to three main smart product design key elements: Technology (T), Drivers (D) and Main Criteria (MC) respectively through prioritising steps in phase one. And also, the given score to each technology benchmarks during the benchmarking phase. Thus, the total readiness score of a company toward Industry 4.0 can be evaluated as follows:

- As given in Eq. (1) the score of each technology (T_i) equals to the achieved score (S_i) multiplied by the weight of that technology (W_{ti}).

$$T_i = S_i \times W_{ti} \qquad (1)$$

- The score of each driver (D_j) equals to the sum of scores of all its constituent technologies multiplied by the weight of the driver (W_{dj}) (see Eq. 2).

$$D_j = W_{dj} \sum_{i=1}^{n} S_i \times W_{ti} \qquad (2)$$

- The score of a main criterion (MC_z) equals to the sum of scores of all its related drivers multiplied by the weight of the main criterion (W_{mcz}) (see Eq. 3).

$$MC_z = W_{mcz} \sum_{j=1}^{k} W_{dj} \sum_{i=1}^{n} S_i \times W_{ti} \qquad (3)$$

Thus, the total score of a company (R) equals the sum of scores of all criteria (MC_z) (see Eq. 4).

$$R = \sum_{z=1}^{h} W_{mcz} \sum_{j=1}^{k} W_{dj} \sum_{i=1}^{n} S_i \times W_{ti} \qquad (4)$$

Where:

h is the number of criteria.

k is the number of drivers and

n is the number of technologies,

The maximum readiness score that a company can achieve is four which means the company is in the position of a *leader*. The minimum score is zero, which represents an *outsider* company. The obtained total score will show the current situation of the company toward Industry 4.0 readiness. Moreover, it gives a clear picture of the company's current situation with respects to each technology, drivers, and main criterion. It should be mentioned that the total readiness score can be any number between 0 and 4. Hence, the following classification can also be provided in which the boundary between the "*outsider* with *beginner*" and "*experienced* with the *leader*" are logically considered to be narrow:

$$\text{If Readiness Score (R)} \begin{cases} 0 < R \leq 0.5 \rightarrow Outsider \\ 0.5 < R \leq 1.5 \rightarrow Beginner \\ 1.5 < R \leq 2.5 \rightarrow Learner \\ 2.5 < R \leq 3.5 \rightarrow Experienced \\ 3.5 < R \leq 4 \rightarrow Leader \end{cases}$$

Beside quantitative readiness score, the visual representation can also be provided to help practitioners in understanding the relative readiness of each main criterion, by technology. For example, Figures 3 illustrates the visual depiction of the SME that is 100% (*Leader*) ready for the transition to Industry 4.0 - all technology benchmarks have been obtained and are therefore highlighted in the chart.

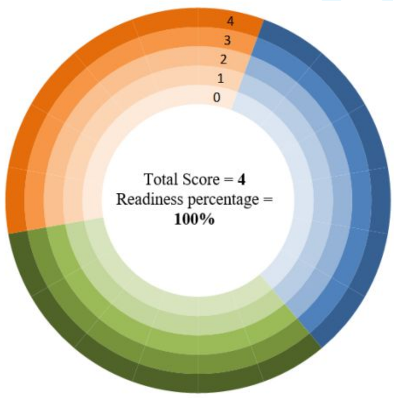

Figure 3. Visual Presentation Example

5. Validation of the proposed hierarchical requirements model for Smart product design development

This Section explains the validation of the proposed model using classical AHP. At first, pairwise comparisons were performed systematically to include all the combinations of main criteria, drivers and technology relationships. For that, a questionnaire was designed for data collection purposes from 30 industrialists belonging to different UK industrial SMEs, who were recognised and selected carefully by the research team as professionals and experts in this particular research area. The questionnaire was developed based on the levels (i.e. main criteria, drivers and technologies) in the proposed hierarchical requirements model for Smart product design development. Experts who have been asked to make pair-wise comparisons between the two factors/criteria in each level at a time, decide which factor is more important and then specify the degree of importance on a scale between one (equal importance) and nine (absolutely more important) of the most important factor/criterion (Saad and Bahadori, 2020). All the responders agreed about the proposed model and showed positive responses towards smart product design and its necessity. Since different participants had different opinions about each criterion, a geometrical mean method was applied to convert the different judgements into one figure for each of the main criterion, the driver and technology (see Eq. 5):

$$\text{Geometric mean} = [(x_1)\,(x_2)\,(x_3)\ldots\,(x_m)]^{1/m} \tag{5}$$

Where

x is the individual weight of each judgment

m is the sample size (number of judgment).

Since the pair-wise comparisons were completed, the next step was to calculate the local priorities from the judgment matrices. The eigenvalue method (EVM) is one of the main calculation methods to derive the priorities from the AHP method (see Eq. 6):

$$AX = \lambda_{max}X \tag{6}$$

Where

A is Comparison matrix

X is Priorities vector

$\boldsymbol{\lambda_{max}}$ is Maximal eigenvalue

In this study, Expert Choice Software was used which follows the EVM process to drive the local priorities of the main criteria, drivers, and technologies. For instance, as shown in figure 4, the judgement of the three main criteria located in top-level was entered. The conclusion was that design real-time data management was the most important criterion (0.493) followed by design system flexibility (0.311), and design execution with the least ranking (0.196). Moreover, the inconsistency rate of the main criteria matrix was 5%, less than the acceptable minimum rate of 10%. Therefore, the inconsistency level is acceptable, and the results show a high level of accuracy.

Figure 4. Main criteria prioritisation and inconsistency measurement

After deriving the local priorities for the main criteria, drivers and technologies through pairwise comparisons, the synthesis analysis has been completed to understand the global priorities of technologies towards the main goal (see Eq. 7).

$$G_{SG} = \sum_{z=1}^{h}\sum_{j=1}^{k} W_{mcz} \times W_{dj} \times W_{tj} \quad (7)$$

Where

$\boldsymbol{G_{SG}}$ is global priorities of the technology with respect to the main goal

$\boldsymbol{W_{tj}}$ is the local weight of the technology with respect to the driver j.

As given in Figure 5, Sensors & Actuators received the highest ranking (16%), followed by Data Mining Technology (11.8%), Software-Based Configurators (10.8%) and Digital Twin (1.1%) was the lowest ranking with respect to the ‘main goal’.

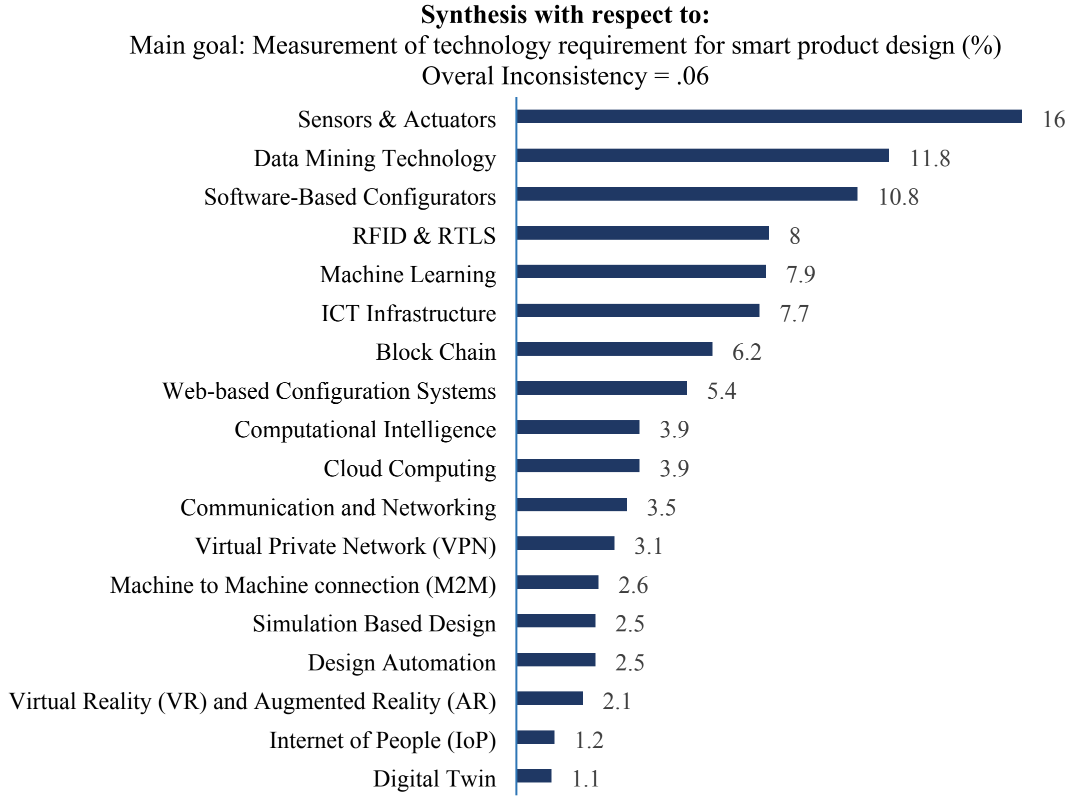

Figure 5. Synthesising the results (%)

6. Industrial application of the proposed SSTRA methodology

In this case, SSTRA was applied by the SME manufacturer in the sanitary ware industry. Due to a confidentiality agreement with the company, the name of the company remains anonymous, but some results can be provided by extracting real names, etc. SSTRA has been implemented with planning a series of meetings and workshops to obtain and analyse the collected data. Due to COVID-19 limitations, all meetings and workshops were conducted online by the Sheffield Hallam University researchers rather than through on-site company visits. Each workshop and meeting took about half a day, totalling approximately 16 hours within a week. Figure 6 illustrates the procedure of the case application.

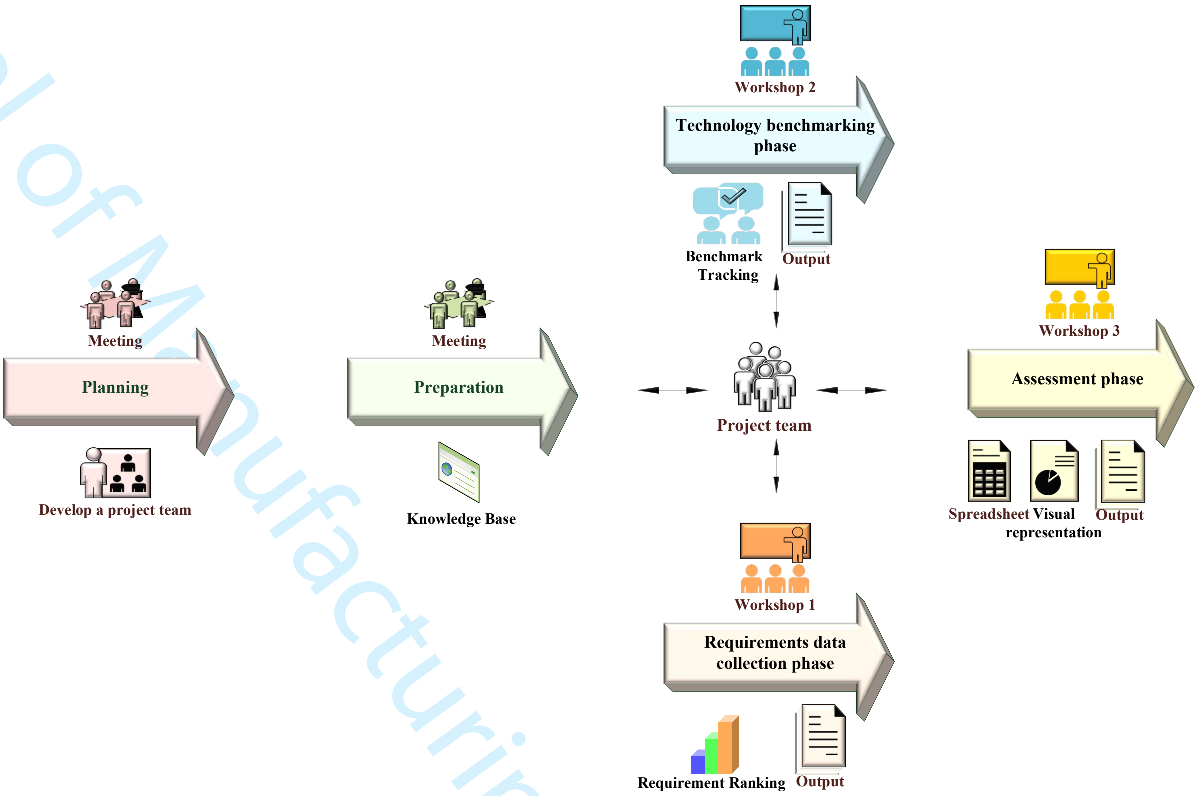

Figure 6. Description of the case application.

The implementation of the SSTRA processes was started by scheduling a series of initial meetings with the company senior managers to decide upon the objective of this practice, the participants and formation of the project team. Senior management formed the project team in the company and appointed the team leader who was responsible for all organisational and logistical issues in the project team. After forming the team, a preparation meeting with all participants was arranged to create a solid knowledge base regarding the SSTRA framework and the matters related to Industry 4.0 within the company.

In the first workshop, during the requirements data collection phase, several exercises were completed. At first, since the focus of this exercise was on smart product design, as the benchmark, the proposed hierarchical requirements model for smart product design development (i.e. Figure 1) was provided to the project team. Then, the project team was requested to evaluate it based on the nature of the SME and its operation and apply any modification if necessary. The research team was available during the workshop for any clarification and support. There was a consensus among the project team members that the benchmark model completely fit with company operation. Subsequently, AHP was utilised to allow company ranking main criteria, drivers and technologies based on its prioritisation. Expert Choice Software was used to drive the local weight of each element of each level in the benchmark model (*i.e.* W_{ti}, W_{dj}, and W_{mcz}). In comparing with data collected from 30 industrial SMEs in the UK (see Section 5), the result shows that there was no significant difference between prioritisations whilst the obtained weights were varied, which is logical. Finally, the output of this phase was documented (see Table IV) to be used through the assessment phase.

[**Table IV** *near here*]

In the second workshop, the technology benchmarking phase was completed by assessing the company technology readiness position based on technologies' benchmarks (*Si*). In this stage, the technologies benchmarks under each driver (Tables III and A1-A8) along with a detailed explanation were provided to assessors for evaluation. The given score to each technology benchmarks was documented (see Table V) and later used as input to the assessment phase to measure the transition readiness.

[**Table V** *near here*]

In the third and final workshop, company readiness was calculated. Equation 4 was used by the assessor team to calculate the total readiness score (R) and identify the company position. The outcome proved that R =1.28, and in this case, the company was classified as "*Beginner*". Besides quantitative readiness score, visual representation of outcomes was also provided to help company decision-makers in understanding the relative readiness of each main criterion by technology (see Figure 7). This valuable information will later play a significant role in guiding and justifying investment in smart product design development R&D projects within the company to achieve the optimum project portfolio.

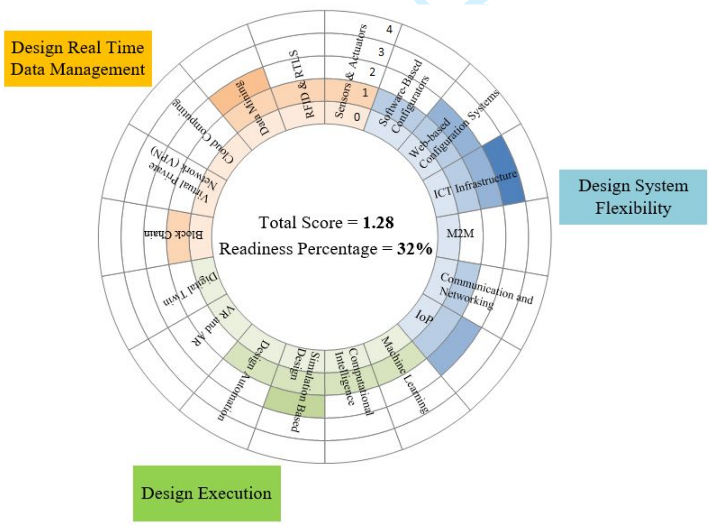

Figure 7. Visual representation of relative readiness of the main criterion.

It is noteworthy that company culture, especially senior management commitment, was a key factor in the success of this application's case. The contribution from inside the company was greatly useful and participants were extremely interested in the Industry 4.0 era. Along with the above factors, having an experienced and motivated team leader in the company made the implementation of this project effective and successful. The result revealed that, while the company implemented a few Industry 4.0 technologies, there is an enthusiasm in owner/senior managers for Industry 4.0 implementation. They have started to change company strategy to employ Industry 4.0 technologies to design and develop a smart product. During the meetings and workshops, some of the terms and equations were not clear to all the practitioners and subsequently, further explanations were provided by researchers. Participants stated that the transparency and simplicity of the SSTRA methodology led to a useful and successful exercise. Thus, considering the integration of SSTRA as a method in the company's transition management activities to Industry 4.0 could improve decision-making effectiveness. The implementation of the SSTRA method, in this case, has confirmed the usability and performance of the SSTRA framework.

7. Conclusion

There is an identified need for developing a maturity/readiness assessment methodology, at the national, industrial sector and the individual enterprise levels, to support SMEs and to have a clear picture in their journey towards Industry 4.0. Hence, in this paper, the SSTRA methodology was developed to provide a systematic approach, with the focus on smart product design; enabling practitioners to assess technology readiness in SMEs toward Industry 4.0.

SSTRA had three phases – a requirement data collection phase, a technology benchmarking phase, and an assessment phase. The SSTRA utilised the AHP to prioritise SME main key criteria, drivers, and technologies. Also, it provided a graphical interface to track technologies' benchmarks under Industry 4.0 TRLs, including the *outsider*, *beginner*, *learner*, *experienced* and *leader*. Furthermore, it introduced a mathematical model to determine the transition readiness and visual representation to help practitioners in understanding the relative readiness of each main area in smart product design development. The feedback collected from the case study revealed the validity and applicability of the method. The company studied showed a willingness to implement SSTRA methodology throughout the company entire value chain (i.e. production planning and control, production engineering, production and product) to support its transition to Industry 4.0.

In contrast, with some existing tools/methods, the proposed methodology allows each SME to evaluate its current situation, with respect to, Industry 4.0 requirements in order to identify what technologies are required to be effectively implemented so as to address the SME operation requirements. Besides this, it provides a clear perspective about SME strengths and weaknesses when determining which areas or technologies need more focus through R&D projects; to keep its products and operation compatible for the competitive market. The implementation of the SSTRA methodology may need to involve more time and resources (e.g. experts, workshops). In return, since it is a step-by-step approach for decision-making, support SMEs to significantly mitigate the risk of further investment and implementation in their journey towards Industry 4.0 benefits.

As a route and map for future research, discussions are underway with the key industrial collaborators from other sectors for further implementation. This provides a more in-depth insight into the pros and cons of the method. Moreover, the proposed tool also would be adopted throughout the end-to-end engineering across the entire value chain. It can assist SMEs to gain valuable information and data throughout the entire value chain and to process it in a standardised manner to analyse the readiness to implement Industry 4.0 in their businesses and operations. Furthermore, the SSTRA can also be aligned with the Strategic Technology Alignment Roadmapping (STAR) methodology (Gindy *et al.*, 2008) to provide guiding and justification of investment in Industry 4.0 transition R&D projects; achieving the optimum project portfolio.

References

Akanmu, A.A., Anumba, C.J. and Messner, J.I., 2012. An RTLS-based approach to cyber-physical systems integration in design and construction. *International Journal of Distributed Sensor Networks*, *8*(12), p.596845.

Akbari, A., Akbari, A., Setayeshmehr, A., Borsi, H. and Gockenbach, E., 2004, November. Software Modules for Monitoring and Diagnosis of Power Transformers. In *Proceedings of the 19th International Power System Conference (PSC 2004), Tehran, Iran* (pp. 22-24).

Akdil, K.Y., Ustundag, A. and Cevikcan, E., 2018. Maturity and readiness model for industry 4.0 strategy. In *Industry 4.0: Managing the digital transformation* (pp. 61-94). Springer, Cham.

Aldridge, M.L., Dill, P.C., Heninger, I.M., Kari, J.D., Marano, C.D. and Urgo, D.M., International Business Machines Corp, 2012. *Dynamic network tunnel endpoint selection*. U.S. Patent 8,261,339.

Anderl, R., Picard, A., Wang, Y., Fleischer, J., Dosch, S., Klee, B. and Bauer, J., 2015. Guideline Industrie 4.0-Guiding principles for the implementation of Industrie 4.0 in small and medium sized businesses. In *Vdma forum industrie* (Vol. 4, pp. 1-31).

Appleton, E., Madsen, C., Roehner, N. and Densmore, D., 2017. Design automation in synthetic biology. *Cold Spring Harbor perspectives in biology*, *9*(4), pp. 1-27.

Arica, E. and Powell, D.J., 2014. A framework for ICT-enabled real-time production planning and control. *Advances in Manufacturing*, *2*(2), pp.158-164.

Automation, R., 2014. The connected enterprise maturity model. *Rockwell Automation*, *12*, pp.1-12.

AVENTICS, 2017, Advanced Valve System. Retrieved from:https://www.aventics.com/media/AVENTICS_USA/Service/Documentation_downloads/Sales_Catalog/AVENTICS_AV-Valves_R499051029.pdf

Bagheri, B., Yang, S., Kao, H.A. and Lee, J., 2015. Cyber-physical systems architecture for self-aware machines in industry 4.0 environment. *IFAC-PapersOnLine*, *48*(3), pp.1622-1627.

Bal, A. and Satoglu, S.I., 2018. Advances in Virtual Factory Research and Applications. In *Industry 4.0: Managing The Digital Transformation* (pp. 235-249). Springer, Cham.

Brettel, M., Friederichsen, N., Keller, M. and Rosenberg, M., 2014. How virtualization, decentralization and network building change the manufacturing landscape: An Industry 4.0 Perspective. *International journal of mechanical, industrial science and engineering*, *8*(1), pp.37-44.

Brusey, J. and McFarlane, D.C., 2009. Effective RFID-based object tracking for manufacturing. *International Journal of Computer Integrated Manufacturing*, *22*(7), pp.638-647.

Canedo, A., 2016, October. Industrial IoT lifecycle via digital twins. In *Proceedings of the Eleventh IEEE/ACM/IFIP International Conference on Hardware/Software Codesign and System Synthesis* (pp. 29).

Commission, E (2018, April) What is an SME?http://ec.europa.eu/growth/smes/business-friendly. Accessed 22 December 2019.

Dai, F., Felger, W. and Göbel, M., 1995. Applying Virtual Reality to Electronic Prototyping—Concept and First Results. In *Virtual Prototyping* (pp. 326-336). Springer, Boston, MA.

Dickerhof, M., 2010, February. A cooperation model and demand-oriented ICT infrastructure for SME development and production networks in the field of microsystem technology. In *International Precision Assembly Seminar* (pp. 319-328). Springer, Berlin, Heidelberg.

Dou, R., Zhang, Y. and Nan, G., 2016. Customer-oriented product collaborative customization based on design iteration for tablet personal computer configuration. *Computers & Industrial Engineering*, *99*, pp.474-486.

Ganzarain, J. and Errasti, N., 2016. Three stage maturity model in SME's toward industry 4.0. *Journal of Industrial Engineering and Management (JIEM)*, *9* (5), pp.1119-1128.

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

Gindy, N., Morcos, M., Cerit, B. and Hodgson, A., 2008. Strategic technology alignment roadmapping STAR® aligning R&D investments with business needs. *International Journal of Computer Integrated Manufacturing*, *21*(8), pp.957-970.

Grosso, C., Trentin, A. and Forza, C., 2014, September. Towards an Understanding of How the Capabilities Deployed by a Web-based Sales Configurator Can Increase the Benefits of Possessing a Mass-Customized Product. In *16th International Configuration Workshop Vicenza, Italy: Università di Padova,* (pp. 81-88).

Hajji, A., Mhada, F., Gharbi, A., Pellerin, R. and Malhamé, R., 2011. Integrated product specifications and productivity decision making in unreliable manufacturing systems. *International Journal of Production Economics*, *129*(1), pp.32-42.

Hermann, M., Pentek, T. and Otto, B., 2016, January. Design principles for industrie 4.0 scenarios. In *2016 49th Hawaii international conference on system sciences (HICSS)* (pp. 3928-3937). IEEE.

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

Huang, T.S. and Chang, C.F., 2005. The role of data mining in the product design and development process. In *Proc. 6th Int. Comput.-Aided Ind. Design Concept Design* (pp. 198-203).

Iglesias-Urkia, M., Orive, A., Barcelo, M., Moran, A., Bilbao, J. and Urbieta, A., 2017, May. Towards a lightweight protocol for Industry 4.0: An implementation based benchmark. In *2017 IEEE International Workshop of Electronics, Control, Measurement, Signals and their Application to Mechatronics (ECMSM)* (pp. 1-6). IEEE.

Jazdi, N., 2014, May. Cyber physical systems in the context of Industry 4.0. In *2014 IEEE international conference on automation, quality and testing, robotics* (pp. 1-4). IEEE.

Jeong, K.S. and Yoo, S.K., 2009. Electro-textile interfaces: Textile-based sensors and actuators. In *Smart Clothing* (pp. 94-118). CRC Press.

Jung, K., Kulvatunyou, B., Choi, S. and Brundage, M.P., 2016. An overview of a smart manufacturing system readiness assessment. In *IFIP International Conference on Advances in Production Management Systems* (pp. 705-712). Springer, Cham.

Konstantinov, S., Ahmad, M., Ananthanarayan, K. and Harrison, R., 2017. The cyber-physical e-machine manufacturing system: Virtual engineering for complete lifecycle support. *Procedia CIRP*, *63*, pp.119-124.

Lau, H.Y.K., Mak, K.L. and Lu, M.T.H., 2003. A virtual design platform for interactive product design and visualization. *Journal of Materials Processing Technology*, *139*(1-3), pp.402-407.

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

Lee, J., Lapira, E., Yang, S. and Kao, A., 2013. Predictive manufacturing system-Trends of next-generation production systems. *IFAC Proceedings Volumes*, *46*(7), pp.150-156.

Lichtblau, K., Stich, V., Bertenrath, R., Blum, M., Bleider, M., Millack, A., Schmitt, K., Schmitz, E. and Schröter, M., 2015. IMPULS-industrie 4.0-readiness. *Impuls-Stiftung des VDMA, Aachen-Köln*.

Löfving, M., Säfsten, K. and Winroth, M., 2014. Manufacturing strategy frameworks suitable for SMEs. *Journal of Manufacturing Technology Management*, *25* (1), pp. 7-26.

Manogaran, G., Thota, C., Lopez, D. and Sundarasekar, R., 2017. Big data security intelligence for healthcare industry 4.0. In *Cybersecurity for Industry 4.0* (pp. 103-126). Springer, Cham.

Marilungo, E., Papetti, A., Germani, M. and Peruzzini, M., 2017. From PSS to CPS design: a real industrial use case toward Industry 4.0. *Procedia Cirp*, *64*, pp.357-362.

Miranda, J., Mäkitalo, N., Garcia-Alonso, J., Berrocal, J., Mikkonen, T., Canal, C. and Murillo, J.M., 2015. From the Internet of Things to the Internet of People. *IEEE Internet Computing*, *19*(2), pp.40-47.

Mittal, S., Khan, M.A., Romero, D. and Wuest, T., 2018. A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises (SMEs). *Journal of manufacturing systems*, *49*, pp.194-214.

Mogos, M.F., Eleftheriadis, R.J. and Myklebust, O., 2019. Enablers and inhibitors of Industry 4.0: results from a survey of industrial companies in Norway. *Procedia CIRP*, *81*, pp.624-629.

Morabito, V., 2017. Business innovation through blockchain. *Cham: Springer International Publishing*.

Pirola, F., Cimini, C. and Pinto, R., 2019. Digital readiness assessment of Italian SMEs: A case-study research. *Journal of Manufacturing Technology Management*.

Rauch, E., Dallasega, P. and Matt, D.T., 2016. The way from lean product development (LPD) to smart product development (SPD). *Procedia CIRP*, *50*, pp.26-31.

Rebentisch, E., Conforto, E.C., Schuh, G., Riesener, M., Kantelberg, J., Amaral, D.C. and Januszek, S., 2018. Agility factors and their impact on product development performance. In *DS 92: Proceedings of the DESIGN 2018 15th International Design Conference* (pp. 893-904).

Rodič, B., 2017. Industry 4.0 and the new simulation modelling paradigm. *Organizacija*, *50*(3), pp.193-207.

Romeo, L., Loncarski, J., Paolanti, M., Bocchini, G., Mancini, A. and Frontoni, E., 2020. Machine learning-based design support system for the prediction of heterogeneous machine parameters in industry 4.0. *Expert Systems with Applications*, *140*, pp.1-15.

Rondini, A., Matschewsky, J., Pezzotta, G. and Bertoni, M., 2018. A simplified approach towards customer and provider value in PSS for small and medium-sized enterprises. In *10th CIRP Conference on Industrial Product-Service Systems, IPS2, Linköping, Sweden* (pp. 61-66). Elsevier.

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

Saad, S.M. and Bahadori, R., 2018. Development of an information fractal to optimise inventory in the supply network. *International Journal of Service and Computing Oriented Manufacturing*, *3*(2-3), pp.127-150.

Saad, S.M. and Bahadori, R., 2020. Logistics capabilities measurement in the fractal supply network. *International Journal of Logistics Systems and Management*, *36*(2), pp.251-281.

Salkin, C., Oner, M., Ustundag, A. and Cevikcan, E., 2018. A conceptual framework for Industry 4.0. In *Industry 4.0: Managing the Digital Transformation* (pp. 3-23). Springer, Cham.

Santos, C., Mehrsai, A., Barros, A.C., Araújo, M. and Ares, E., 2017. Towards Industry 4.0: an overview of European strategic roadmaps. *Procedia Manufacturing*, *13*, pp.972-979.

Santos, R.C. and Martinho, J.L., 2019. An Industry 4.0 maturity model proposal. *Journal of Manufacturing Technology Management*.

Schlechtendahl, J., Keinert, M., Kretschmer, F., Lechler, A. and Verl, A., 2015. Making existing production systems Industry 4.0-ready. *Production Engineering*, *9*(1), pp.143-148.

Schumacher, A., Erol, S. and Sihn, W., 2016. A maturity model for assessing Industry 4.0 readiness and maturity of manufacturing enterprises. *Procedia Cirp*, *52*(1), pp.161-166.

Shephard, M.S., Beall, M.W., O'bara, R.M. and Webster, B.E., 2004. Toward simulation-based design. *Finite Elements in Analysis and Design*, *40*(12), pp.1575-1598.

Siddique, N. and Adeli, H., 2013. *Computational intelligence: synergies of fuzzy logic, neural networks and evolutionary computing*. John Wiley & Sons.

Simons, S., Abé, P. and Neser, S., 2017. Learning in the AutFab–the fully automated Industrie 4.0 learning factory of the University of Applied Sciences Darmstadt. *Procedia Manufacturing*, *9*, pp.81-88.

Stock, T. and Seliger, G., 2016. Opportunities of sustainable manufacturing in industry 4.0. *Procedia Cirp*, *40*, pp.536-541.

Torn, I.A.R. and Vaneker, T.H., 2019. Mass Personalization with Industry 4.0 by SMEs: a concept for collaborative networks. *Procedia Manufacturing*, *28*, pp.135-141.

Uhlemann, T.H.J., Lehmann, C. and Steinhilper, R., 2017. The digital twin: Realizing the cyber-physical production system for industry 4.0. *Procedia Cirp*, *61*, pp.335-340.

Vaidya, S., Ambad, P. and Bhosle, S., 2018. Industry 4.0–a glimpse. *Procedia Manufacturing*, *20*, pp.233-238.

Wang, S., Wan, J., Zhang, D., Li, D. and Zhang, C., 2016. Towards smart factory for industry 4.0: a self-organized multi-agent system with big data based feedback and coordination. *Computer Networks*, *101*, pp.158-168.

Witkowski, K., 2017. Internet of things, big data, industry 4.0–innovative solutions in logistics and supply chains management. *Procedia Engineering*, *182*, pp.763-769.

Wu, D., Rosen, D.W. and Schaefer, D., 2014. Cloud-based design and manufacturing: status and promise. In *Cloud-based design and manufacturing (CBDM)* (pp. 1-24). Springer, Cham.

Yin, Y. and Qin, S.F., 2019. A smart performance measurement approach for collaborative design in Industry 4.0. *Advances in Mechanical Engineering*, *11*(1), pp.1-15.

Zawadzki, P. and Żywicki, K., 2016. Smart product design and production control for effective mass customization in the Industry 4.0 concept. *Management and Production Engineering Review*, *7*(3), pp.105-112.

Appendix 1:

[**Table A1** *near here*]

[**Table A2** *near here*]

[**Table A3** *near here*]

[**Table A4** *near here*]

[**Table A5** *near here*]

[**Table A6** *near here*]

[**Table A7** *near here*]

[**Table A8** *near here*]

List of Tables

Table I. Nine pillars of Industry 4.0

Pillar	Description and goal
Big Data and Analysis	• Gathering and understanding data from all involved parties (manufacturing, supplier, customer). • Useful for learning from previous processes/improvements and predicting future conditions (Bagheri *et al*., 2015). • Important factors: volume, variety, the velocity of generation and analysis, the value of data (Witkowski, 2017).
Autonomous Robots	• Higher precision than humans (Vaidya *et al*., 2018). • Can work in difficult conditions or work with humans. • More intuitive by e.g. learning quickly from humans.
Simulation	• The central requirement for self-aware systems to contextualise data (Rüßmann *et al*., 2015). • Essential to predict consequences of proposed improvements (Simons *et al*., 2017). • Self-optimisation by comparison of simulated and real data.
System Integration	• Horizontal integration across the value creation network (Saad and Bahadori, 2018). • Vertical integration in the manufacturing plant. • End-to-end across the product life cycle (Stock and Seliger, 2016)
(Industrial) Internet of Things (IoT)	• The network of connected objects that can communicate using standardised protocols (Hozdić, 2015). • Context, omnipresence, and optimisation are key factors. • Builds the infrastructure of interconnected machines and sensors to acquire data and act upon it (Schumacher *et al*., 2016).
Cyber-Physical Systems (CPS) and Cyber Security	• Integration between machine and humans with computation, communication, and control systems (Bagheri *et al*., 2015). • Decentralisation and autonomous behaviour are key characteristics (Vaidya *et al*., 2018). • Secure and reliable communication is required for the network to work as intended (Rüßmann *et al*., 2015).
Cloud Computing	• The platform that allows all the involved parties to share and access data (Marilungo *et al*., 2017). • Must be fast and reliable (in real-time).
Additive Manufacturing	• New efficient product design possibilities with reduced time to market. • Increased individualisation.
Augmented Reality (AR)	• Enables flexible communication between machines and humans. • Drastically optimises and reduces the required training for many tasks.

Table II. Summary of the Literature Review

Author(s)	Maturity/readiness dimensions and levels /Assessment method/ scope	Applicability to SMEs
Lichtblau *et al.* (2015)	6 dimensions along with 18 sub-dimensions to classify company readiness in the six levels of readiness. The online assessment tool is provided. The focus was on the manufacturing industry	No
Schumacher *et al*. (2016)	9 dimensions and 62 evaluation items for 5 levels of the maturity model. The assessment questionnaire is used. Focused on the manufacturing industry.	Yes
Rockwell Automation (2014)	5 stages maturity model with 4 different technological dimensions. The assessment method is not provided. IT capabilities of the company were the main focus.	Vague
Akdil *et al.* (2018)	4 levels of maturity and 3 dimensions. The assessment questionnaire is provided and deployed in a retail company	No
Ganzarain and Errasti (2016)	3 stages of maturity along with 5 steps. The self-assessment method is proposed. The focus mainly was on the SMEs culture, staff skills and technology.	Yes
Jung *et al*. (2016)	4 dimensions for assessing smart manufacturing readiness in SMEs. Validated using statistical analysis.	Vague

Table III. Data acquisition technologies benchmarks

Data Acquisition					
	Benchmark				
Technology	***Outsider*** **(*S*=0)**	***Beginner*** **(*S*=1)**	***Learner*** **(*S*=2)**	***Experienced*** **(*S*=3)**	***Leader*** **(*S*=4)**
Sensors & Actuators	No use of sensors & actuators ☐	Sensors & actuators are integrated but they are offline. ☐	Sensor readings are sent by the product to the design system. ☐	Sensor readings are processed by the product and are sent to the design system in real-time. ☐	Sensor readings are processed by the product/ data are exchange by the product in real-time (the product is fully connected to the design system) ☐
RFID & RTLS	No use of RFID & RTLS ☐	RFID is integrated and the product can be identified uniquely. ☐	RTLS is integrated and the product sends its location. ☐	RFID & RTLS are integrated and the product exchange data and location in real-time. ☐	RFID & RTLS are fully integrated and the product exchange data and location in real-time / its entire life cycle is traceable. ☐

Table IV. The output of requirements data collection phase

Main Criteria (MC)	W_{mcz}	Driver (D)	W_{dj}	Technology (T)	W_{ti}
Design Real Time Data Management	0.46	Data Acquisition	0.57	Sensors & Actuators	0.67
				RFID & RTLS	0.33
		Data Analytics	0.29	Data Mining Technology	0.75
				Cloud Computing	0.25
		Data Security	0.14	Virtual Private Network (VPN)	0.33
				Blockchain	0.67
Design System Flexibility	0.29	Collaborative Customisation	0.25	Software-Based Configurators	0.50
				Web-based Configuration Systems	0.50
		Agility	0.50	ICT Infrastructure	0.75
				Machine to Machine connection (M2M)	0.25
		Collaborative Design	0.25	Communication and Networking	0.50
				Internet of People (IoP)	0.50
Design Execution	0.25	Decision Making	0.41	Machine Learning	0.67
				Computational Intelligence	0.33
		Modelling	0.33	Simulation Based Design	0.50
				Design Automation	0.50
		Prototyping	0.26	Virtual Reality (VR) and Augmented Reality (AR)	0.67
				Digital Twin	0.33

Table V. The output of the Technology benchmarking phase

Technology (T)	S_i
Sensors & Actuators	1
RFID & RTLS	1
Data Mining Technology	2
Cloud Computing	0
Virtual Private Network (VPN)	0
Blockchain	1
Software-Based Configurators	1
Web-based Configuration Systems	2
ICT Infrastructure	3
Machine to Machine connection (M2M)	0
Communication and Networking	1
Internet of People (IoP)	2
Machine Learning	1
Computational Intelligence	1
Simulation-Based Design	2
Design Automation	1
Virtual Reality (VR) and Augmented Reality (AR)	0
Digital Twin	0

Table A1. Data Analytics technologies benchmarks

Data Analytics					
Benchmark					
Technology	***Outsider* (*S*=0)**	***Beginner* (*S*=1)**	***Learner* (*S*=2)**	***Experienced* (*S*=3)**	***Leader* (*S*=4)**
Data Mining Technology	No use of data mining technology ☐	Data is collected and saved in the product / analysed data are not used for the new design. ☐	Data is collected, analysed, and saved in the product / analysed data are not used for new designing in real-time. ☐	Data is collected, analysed, and used for new design in real-time / Patterns are discovered to develop a new design. ☐	Discovered patterns are used for new design in real-time / New design specifications are predicted by the system. ☐
Cloud Computing	No use of Cloud computing ☐	The product shares the data through Cloud just with the design system. ☐	The product shares data through Cloud with the design system and internal stakeholders in real-time. ☐	Data is computed and analysed by Cloud system in real-time / Valuable data are sent to the design system to develop the new design in real-time. ☐	Design system has full access to the product in real-time/ The product can share necessary information with all stakeholders in real-time. ☐

Table A2. Data Security technologies benchmarks

Data Security					
			Benchmark		
Technology	***Outsider* (*S*=0)**	***Beginner* (*S*=1)**	***Learner* (*S*=2)**	***Experienced* (*S*=3)**	***Leader* (*S*=4)**
Block-chain	No use of block-chain ☐	The design team can track the product from the design stage to the delivery stage through a secure blockchain-backed system. ☐	Internal stakeholders (IS) can track the product from the design stage to delivery stage through a secure blockchain-backed system (e.g. the proof-of-work system) ☐	Internal and External stakeholders (ES) can track the product from the design stage to the delivery stage through a secure blockchain-backed system. ☐	IS, ES and customers can track the product from the design stage to delivery stage through secure a blockchain-backed system. ☐
Virtual Private Networks (VPN)	No use of virtual private network ☐	The product can create VPNs. ☐	The IS and EX are connected through remote-access VPNs company through VPNs. ☐	The IS and EX are connected to the design system through Site-to-site VPNs. ☐	The IS, EX and products are connected through Site-to-site VPNs. ☐

Table A3. Collaborative Customisation technologies benchmarks

Collaborative Customisation					
	Benchmark				
Technology	***Outsider*** **(*S*=0)**	***Beginner*** **(*S*=1)**	***Learner*** **(*S*=2)**	***Experienced*** **(*S*=3)**	***Leader*** **(*S*=4)**
Software-Based Configurator	No use of the software-based configurator ☐	Specific software is developed for the product customisation, but it is the initial phase. ☐	Customer can customise the product to a very limited extent such as the colour of the product through software. ☐	Customer can customise the product to a good extent through software such as in assembly level of the product. ☐	Customers can customise fully the product by software-based configurators. ☐
Web-Based Configurator	No use of the web-based configurator ☐	A specific software website is for the product customisation, but it is the initial phase. ☐	Customer can customise the product to a very limited extent such as the colour of the product through the website. ☐	Customer can customise the product to a good extent through the website such as in assembly level of the product. ☐	Customers can customise fully the product through the company's website. ☐

Table A4. Agility technologies benchmarks

Agility					
	Benchmark				
Technology	***Outsider* (*S*=0)**	***Beginner* (*S*=1)**	***Learner* (*S*=2)**	***Experienced* (*S*=3)**	***Leader* (*S*=4)**
ICT Infrastructure	Information exchange via email/telecommunication ☐	Central data servers in production ☐	Information exchange via the company intranet ☐	Automated information exchange within the company ☐	Industry 4.0 virtual enterprise ☐
Machine to Machine Connection (M2M)	No communication ☐	Connection in each department through Industrial Ethernet ☐	Connection in all departments through Industrial Ethernet, just inside the company ☐	The connection between company and supplier through the internet, but exchange data with human interaction and periodically ☐	The connection between company and supplier through the internet, and exchange data in real-time autonomously ☐

Table A5. Collaborative Design technologies benchmarks

Collaborative Design					
	Benchmark				
Technology	***Outsider* (*S*=0)**	***Beginner* (*S*=1)**	***Learner* (*S*=2)**	***Experienced* (*S*=3)**	***Leader* (*S*=4)**
Communication & Networking	Product design is just the R&D department task. ☐	To develop the product, other departments of the company participate but to a very limited extent. ☐	To develop the product, other departments of the company participate dynamically to a good extent and the head of the company participate actively. ☐	To develop a product whole company and supplier participate ☐	To develop a product whole company, supplier and customer participate ☐
Internet of People (IoP)	No use the Internet of People (IoP) ☐	Just the R&D department are connected by IoP ☐	All members of the company connected by IoP ☐	All members of the company and supplier are connected by IoP ☐	All members of the company, supplier and customer are connected by IoP ☐

Table A6. Decision-making technologies benchmarks

Technology	***Outsider* (*S*=0)**	***Beginner* (*S*=1)**	***Learner* (*S*=2)**	***Experienced* (*S*=3)**	***Leader* (*S*=4)**
Decision making					
	Benchmark				
Machine Learning	No use Machine Learning ☐	Machine learning is used just to find patterns in exist data in the company. ☐	Machine learning is used just to find out existing patterns in the market. ☐	Machine learning is used just to find out existing patterns in the market and classifying customers' current wishes and wants. ☐	Machine learning Tech. fully employed and is used to find patterns in the market and predicting customers' wishes and wants. ☐
Computational Intelligence	No use of Computation al Intelligence ☐	Computational Intelligence is used just to do repeated tasks in the design and development phase. ☐	Computational Intelligence is used to develop better product specifications to a limited extent and based on company's needs. ☐	Computational Intelligence is used to develop better product specifications-based customers behaviour and implementing customers' current wishes and wants. ☐	Computational Intelligence fully employed and is used to design and develop a product and predict the future specification of the product based on customers' wishes and wants. ☐

Table A7. Simulation Modelling technologies benchmarks

Simulation Modelling					
Benchmark					
Technology	***Outsider* (*S*=0)**	***Beginner* (*S*=1)**	***Learner* (*S*=2)**	***Experienced* (*S*=3)**	***Leader* (*S*=4)**
Simulation-Based Design (SBD)	No use of SBD ☐	The product is simulated by the design group to a very limited extent just to assess if the redesign is needed. ☐	The product periodically (i.e. monthly) is simulated by the design group to get the best design for it and redesigning is executed periodically. ☐	The product dynamically is simulated by the design group to get the best design for it and redesigning is executed dynamically. ☐	SBD tech is employed fully, and the product dynamically is simulated autonomous to get the best design for it. ☐
Design Automation (DA)	No use of DA ☐	The machine is used to do simple tasks only and almost all design process is done by human. ☐	The machines are used just a limited extent and most of the design process is done by human. ☐	The design process is done to a good extent by machine but still, human interaction is needed to finalise the design. ☐	The complete design process is done by the machine autonomously without no human interaction. ☐

Table A8. Prototyping technologies benchmarks

Prototyping					
	Benchmark				
Technology	***Outsider* (*S*=0)**	***Beginner* (*S*=1)**	***Learner* (*S*=2)**	***Experienced* (*S*=3)**	***Leader* (*S*=4)**
Virtual Reality (VR) & Augmented Reality (AR)	No use of Virtual Reality & Augmented Reality ☐	Capture video by using digital image processing. ☐	The new product can be tested in a virtual environment and some AR features are employed but limited. ☐	Design and testing process happens in the virtual world to a good extent but still, some tasks needed to be done in real-world and designers use AR to a good extent in the development and design process ☐	The whole design and testing process happen in the virtual world and designers use AR fully in the development and design process. ☐
Digital Twin	No use of digital twin ☐	Offline digital twin ☐	The digital twin is connected to the product but data exchange with delay (in a specific period e.g. monthly) ☐	Digital Twin is connected to the product and they interact in real-time. ☐	Digital Twin is connected to the product and they interact in real-time / New design specifications are used for digital twin based on the product situation. ☐