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THE IMPACT OF THE DIGITAL ERA ON THE IMPLEMENTATION OF THE TRADITIONAL SIX-SIGMA DMAIC- A NEW DMAISE CYCLE DEVELOPMENT

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There is a clearly identified need for adjusting the current implemented standards and methods in the area of process improvement, like Six Sigma, to be aligned with technology advances in the context of Industry 4.0. Thus, this research aims to focus on the Six Sigma DMAIC methodology and introduce a new quality improvement cycle toward Industry 4.0. The proposed new Six Sigma implementation procedure is called the DMAISE (Pronunciation: də-mɛ́jz/də-mayz) improvement cycle, which consists of five main phases: Data Measurement, Analysis, Interpretation, Simulation and Enhancement. DMAISE cycle is introduced to obtain all benefits from the DMAIC while not being affected by its limitations that result from the lack of proper integration of technologies available through the advancements inspired by Industry 4.0. A questionnaire survey is developed to collect data from practitioners, experienced employees, and academics in the available organisations to evaluate and validate the proposed new cycle. The results demonstrated that the proposed cycle is considered a viable quality improvement cycle for the new challenges that arise with the Industry 4.0/digital era and the smart technologies being developed for manufacturing environments.

Keywords: Industry 4.0, Six Sigma, DMAIC, DMAISE Quality Improvement, Performance Evaluation.

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1. INTRODUCTION

Industry 4.0 is the newest industrial revolution introduced in 2011 by the Federal Ministry of Education and Research Germany (BMBF) to describe the trend of interconnectivity and digitalisation in manufacturing embodied in cyber-physical systems (Kagermann *et al*., 2011). Industry 4.0 comes as a successor to three former industrial revolutions, all related to the introduction of the steam engine, mass production with the aid of electrical power and automation using IT and electronics (Mogos *et al*., 2019). It highlights the importance of new and innovative technologies being readily available to businesses in the twenty-first Century (Morgan 2019). Industry 4.0 has been discussed as a novel model for achieving intermittent manufacturing by dramatically improving mass production's productivity through automation and digitisation (Tamás and Illés, 2016; Chiarini and Kumar, 2020). It 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 (Saad *et al*., 2021). It promises to offer enormous opportunities for future production, including modular, efficient, and intelligent manufacturing systems that allow the creation of customised products in a batch size of one with the same economic conditions as mass-producing them (Lasi *et al*., 2014; Sony and Naik, 2020). Industry 4.0 can significantly improve customer satisfaction by eliminating defective products and providing better services (Chiarini and Kumar, 2020). Unlike the conventional system, which focuses on optimising production processes, Industry 4.0 seeks to optimise each specific product (Valdeza *et al*., 2015). Since optimisation requires zero defects, quality management is required to achieve this goal (Lee *et al*., 2019). Hence, the need for integration of Industry 4.0 technologies and concepts with continuous improvement practices to get the maximum benefit from available resources has been stressed in the literature (e.g., Vlachos *et al*., 2021; Tortorella *et al*., 2022; Chiarini *et al*., 2020; Antony *et al*., 2019; Vinodh *et al*., 2020; Chiarini and Kumar 2020; Skalli *et al*., 2023).

Six Sigma is one of the most widely used continuous process improvement methods to achieve operational excellence. It was initially created for the electronics industry in the 1980s as a systematic problem-solving approach consisting of steps to identify problems and customer needs, reduce the likelihood of process errors, and increase productivity (Kwak and Anbari, 2006). Six Sigma has since extended its importance in numerous other industries, including general manufacturing and service industries like governments and hospitals, due to its rigid structure and step-by-step instructions (Tjahjono *et al*., 2010;

Antony *et al*., 2012). It represents the probability (or percentage) of defect-free products in the output. A defect thereby represents every possible cause of customer dissatisfaction (Seow and Antony, 2004). In this case, Six Sigma describes a success rate of 99.99966% or 3.4 Defects-Per-Million-Opportunities (DPMO) (Li *et al*., 2011). This low number can be achieved by reducing variation in the process until enough products are within the upper and lower specification limit that is required by the customer (Paul, 1999). The final goal is the reduction of variance and, thus, higher customer satisfaction due to higher quality. As a process improvement tool, Six Sigma focuses on improving established processes using specific techniques such as the DMAIC cycle and examines quality management through advanced statistical methods (Chiarini and Kumar, 2020). The word DMAIC is the abbreviation of the five phases, including *Define*, *Measure*, *Analyse*, *Improve* and *Control* (Foster, 2007):

- *Define*: In this phase, the needs and expectations of internal and external customers and the technical requirements of the process are stated, and the products and processes that need to be improved are identified.
- *Measure*: In this phase, the expected performance of the process and the current state of the process are determined. Input and output variables of the process are defined, and measurement systems are evaluated.
- *Analyse*: In the analysis phase, the data is analysed, and the most important input and internal factors of the process that affect the process outputs are identified.
- *Improve:* At this phase, activities and improvements that lead to the optimisation of process outputs and the elimination of downtime and changes in the process are identified.
- *Control:* Finally, in this phase, the acquired advancements are secured, and guidelines to prevent similar issues in the future are provided.

Industry 4.0 generates in-process data streams that traditional Six Sigma approaches are not applicable in such an environment (Giannetti and Ransing, 2016). Six Sigma DMAIC is limited in the scope of data collection and analysis due to the manual process of problem definition and measurement, restricted intelligence, and a narrow overview of humans overseeing the process (Ghosh and Maiti, 2014). However, the new technologies incorporated in Industry 4.0, such as Machine Learning and Big Data, can detect system-wide issues or untapped potential in real-time and automate the continuous improvement process to apply it in areas that could not be examined yet (Gupta *et al*., 2020). The concept of Industry 4.0 promises significant enhancements in process improvement due to large quantities of available data, new possibilities of data analytics using simulation, and advanced technologies (Tamás and Illés, 2016). Undoubtedly, this development will change conventional quality improvement techniques like Six Sigma to be applied in the future. Hence, the main aim of this research work is to develop a new methodology called the DMAISE Cycle to adjust currently implemented standards and methods to improve the processes using the knowledge of technologies that will be universal very shortly.

This research work has been conducted at Sheffield Hallam University (SHU) by the Integrated Manufacturing, I4.0 & Supply Chain Management Research Group and serves the purpose of indicating the necessary changes to the quality improvement tool Six Sigma and the associated DMAIC cycle when combined with the new technologies of Industry 4.0. The remainder of the paper is organised as follows: In the next section, the new Six Sigma DMAISE improvement cycle with its concurrent processes, outputs and technologies is proposed. In section 3, the validation of the proposed cycle is presented. Then, the paper ends with overall conclusions and a discussion.

2. THE PROPOSED SIX-SIGMA DMAISE CYCLE

As mentioned above, this paper aims to reinvent the DMAIC cycle with all the advantages it offers while not being affected by its limitations that result from the lack of proper integration of technologies available through the advancements inspired by Industry 4.0. The new proposed Six Sigma improvement cycle is named DMAISE. The word DMAISE is the abbreviation of the five phases of the quality improvement cycle towards Industry 4.0, which comprises *Data Measurement*, *Analyse*, *Interpretation*, *Simulation* and *Enhancement*. A comparison and overview of DMAIC vs. DMAISE are illustrated in Figure 1.

In the rest of this section, the proposed DMAISE cycle is explained in detail, and the following colour code is used to facilitate the understanding of the cycle: Every phase (blue) may consist of the number of processes (orange), decisions (purple) and outputs (grey) along with required technologies (red). They are introduced individually at first and then combined in the final DMAISE diagram.

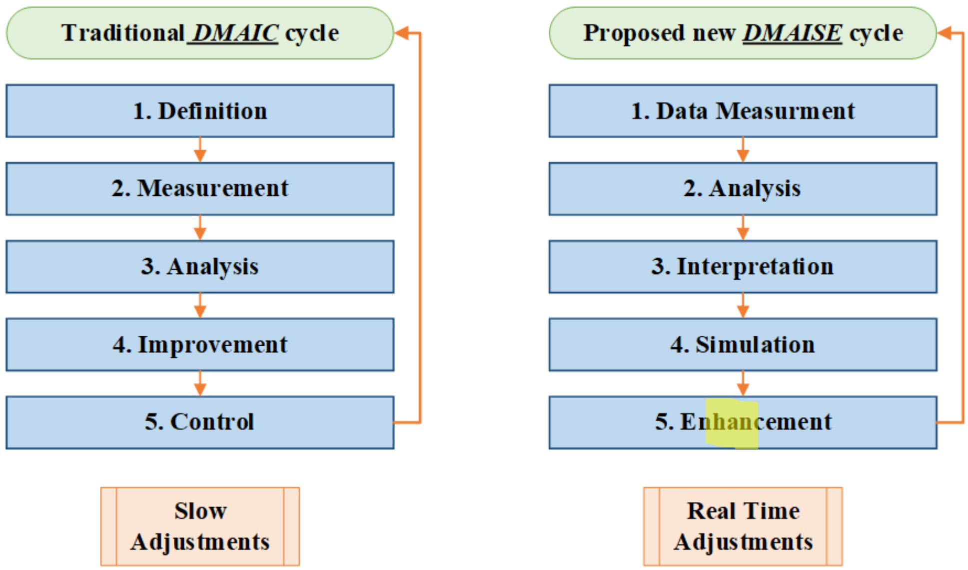

Figure 1. Comparison of traditional DMAIC and proposed DMAISE cycle

2.1 Data Measurement Phase

The sequence of the proposed DMAISE cycle is started by measuring the data instead of defining the problem first. Through conventional manufacturing systems, data are documented on paper, while with the recent development, integrated information technology with manufacturing along with 'computerised systems utilisation' allows machines to collect and save data simultaneously (Farsi and Zio, 2019). Hence, during the *Data Measurement* phase, as shown in Figure 2, the machines collect and log the data, while a Measurement System Analysis (MSA) is conducted independently to ensure data reliability.

The effectiveness of Industry 4.0 depends on the data that is collected as well as the intelligent systems that are used to conclude and decide what the information means. The fundamental tool enabling a cyber-physical system (CPS) is thus the infrastructure that allows reliable data collection in real-time (Lee *et al*., 2015). This data is collected internally and externally using many sensors and a kind of identification technology like Radio-Frequency Identification (RFID) and Real-time Locating Systems (RTLS) that are connected through the network commonly referred to as the Internet of Things (Zhang *et al*., 2016). This provides an accurate representation of inputs, process characteristics and outputs to portray the machines and processes while being tether-free and compatible with different types of data or protocols (Vijayaraghavan *et al*., 2008). Considering the amount of data that is constantly produced by this network of sensors, the collection and analysis using Big Data is the next critical factor to reaching a successful quality improvement process (Lee *et al*., 2014). This goes hand in hand with a reliable integration of Cloud Computing to store and access the data flexibly and allow easy adjustments as well as the possibility to access it from anywhere. However, it is essential to have a sophisticated Cybersecurity implementation ensuring that only authorised parties have access (Bagheri *et al*., 2015; Rüßmann *et al*., 2015). The output of this phase is a Plant Snapshot that exactly reflects the condition of every component in the plant at one specific moment (Lee *et al*., 2015).

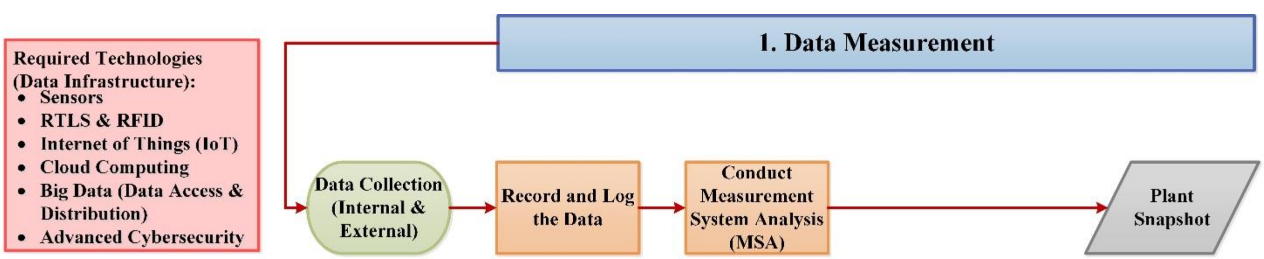

Figure 2. Illustrates the contents of the data measurement phase, including its required technologies, processes, and output.

2.2 Analysis Phase

After the data measurement, the next phase is *analysis*, which is critical to analyse data properly and turn it into usable information. To prepare for the analysis, the data must be cleaned properly to avoid noise, incomplete data sets or simply correct errors that have been detected (Zhang *et al*.,2003). Machine Learning (ML) and Data Mining serve the purpose of categorising the data (Oussous *et al*., 2017), thus enabling the conversion from data to usable information (Lee *et al*., 2015). Humans are not able to cope with the significant amount of data that is collected (Dogan and Gurcan, 2018), let alone analyse it in real-time. Recent developments in the area of algorithms have significantly improved the capabilities of ML, which can capture and process large amounts of data at high velocity (Günther *et al*., 2017). Newly developed systems must be fed with available data that is cleaned, categorised and selected. Data cleaning and categorisation are essential in this stage since this enables the detection of patterns using advanced statistics (Larose, 2005). Considering the amount of information that must be analysed, the degree of optimisation for this system to achieve a real-time data analysis is crucial for avoiding unintentional disruptions in the processes. This offers flexibility and responsiveness that cannot be achieved with current technologies. The basic extraction of information from the collected data is referred to as Data Mining and comprises two common techniques: descriptive and predictive data mining (Han *et al*., 2011). The descriptive type is applied for clustering and associating data that allows categorisation into groups by looking for common rules. The predictive type goes one step further and is used to classify these categories according to predefined classes representing the importance and enabling prediction (Han *et al*., 2011). This information can then be further processed and analysed to determine the dependencies of variables Critical to Quality factors (CTQs) and Key Performance Indicators (KPIs). Traditionally, this was a process that involved manually selecting the measured data and then using statistical analysis software, brainstorming, as well as cause and effect diagrams for the analysis (Srinivasan *et al*., 2016). Especially these processes are perfect examples of how the capabilities of Industry 4.0 can optimise the output of a Six Sigma step since they enable the automated recognition of patterns in data sets that cannot be analysed manually by humans (Wu *et al*., 2017; Teti *et al*., 2010).

The classical statistical analysis programs are static and can, therefore, only handle a limited amount of data. Moreover, they must be told what to investigate, while humans then interpret the results using tools like Pareto analysis. Advanced statistical analysis, on the other hand, will be able to autonomously detect these patterns in a greater pool of available information and thus make it possible to achieve enhancements that nowadays remain undetectable. Next, by integrating the RFID and conventional Value Stream Mapping (VSM), Dynamic Value Stream Mapping (DVSM) is created that provides real-time information regarding the inputs and outputs of every machine and process (Ramadan *et al*., 2012). Consequently, the output of the phase is a list of confirmed root-causes for lower KPIs and the relationship between the identified variables. Figure 3 demonstrates the processes included in the adjusted Analysis phase along with the required technologies.

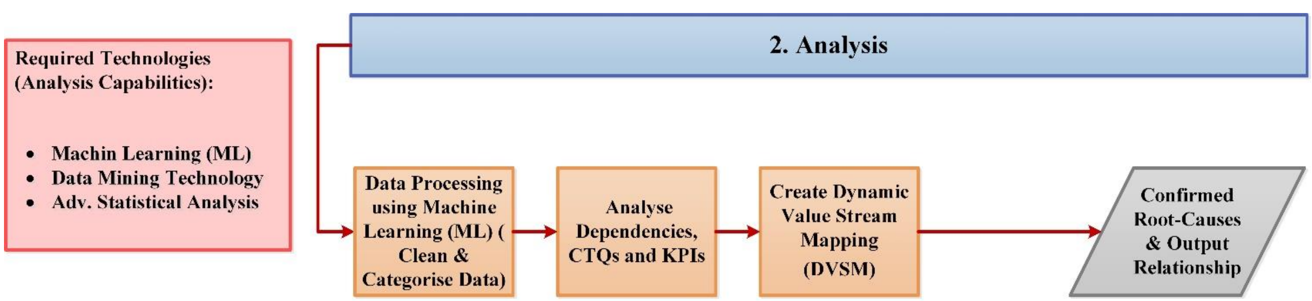

Figure 3. Illustrates the contents of the analysis phase, including its required technologies, processes, and output.

2.3 Interpretation Phase

The *Interpretation phase* in the DMAISE cycle replaces the traditional *Define* phase in DMAIC and is thus responsible for deciding which problems are going to be solved. As illustrated in Figure 4, the first stage is defining the internal and external constraints that result from limitations of the company and resources like machines, employees and equipment or the suppliers, logistics, laws, etc. Consequently, these limitations outline the best achievable performance in the context of the company's goals and objectives. This is followed by a comparison of this optimal condition with the status quo and the interpretation of the difference into necessary changes of process variables. Next is to define target variables and process robustness. According to Gianetti (2017), process robustness defines the ability of a product to fulfil the customer's requirements despite variances in the process input. With the amount of available internal and external data (e.g., usage information from customers) and advanced software capabilities, it is possible to adjust the required upper and lower specification limits to improve the operations capabilities (Gianetti and Ransing, 2016). This adaptation of the accepted tolerance improves the cost-effectiveness of the process. However, traditional models do not adequately represent real systems due to the 'non-linear interactions' (Ransing *et al*., 2015) between a high number of variables. This phase requires a self-aware Artificial Intelligence (AI) that can contextualise the information regarding production characteristics. In this case, it almost acts like an advanced Enterprise Resource Planning (ERP) and Master Production Schedule (MPS), which is equipped with human intuition and the resources of increased computational power and storage to cope with the available information. If it recognises any significant changes in the priorities, it will reiterate the KPIs that have been specified in the previous *Analysis phase*. Also, many researchers believe that even though automation will be unavoidable, some tasks will still require human intervention (Vaidya *et al*., 2018). This leads to the belief that it is important to offer a new and improved kind of communication between humans and machines.

The communication between humans and machines must be efficient and intuitive. The classical Human Machine Interfaces (HMI) that can be found on machines or ERP systems are generally receipts of an order that has been mechanically input using keyboard-like buttons and displays feedback from the process and ways of interacting with the system on a 2D screen (Gorecky *et al*., 2014). However, due to current advancements, it has changed to advanced devices such as 'touch interfaces, voice interfaces, gesture interfaces, and virtual and augmented reality glasses' (Farsi and Zio, 2019). Many companies are now using Virtual Reality (VR) and Augmented Reality (AR) to offer new ways of increasing efficiency and improving development. Maintenance and repair can be a good example of which operator, by using VR/AR glasses, would be able to simply monitor the machine's performance parameters and adjust it without even physically touching it (Farsi and Zio, 2019). These technologies also decrease the need for training new employees by integrating them more effortlessly into new processes and training them to decrease the production ramp-up and test new procedures that rely on human actions digitally (Schmitt *et al*., 2013). At the end of the *Interpretation phase*, all the process goals regarding the three critical categories (Quality, Cost and Time) will be defined.

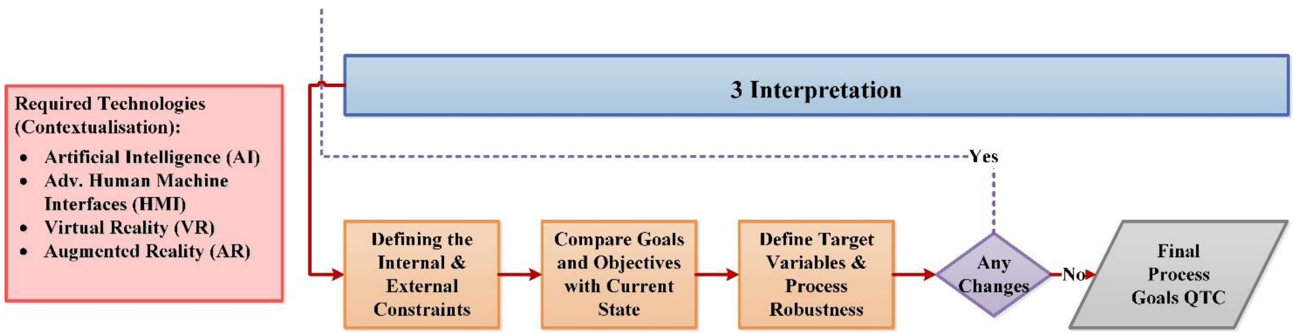

Figure 4. Illustrates the contents of the interpretation phase, including its required technologies, processes and output

2.4 Simulation Phase

The next phase is *Simulation*, which is key to the future of process improvement strategies (Rüßmann *et al*., 2015). The application of simulations avoids the high costs of pilot experiments due to additional training or readjustments of processes and machines that might not improve the output (Badakhshan *et al*., 2020). At the first stage of this phase, the simulation models under-measured data in the previous phases need to be adjusted. With the additional information available through the collected data and the advancements in AI as well as computation power, the difference between simulated models, scenarios and reality can shrink to a negligible factor. These high-accuracy simulation models are already being implemented in the industry and are commonly referred to as Digital Twins (Uhlemann *et al*., 2017), which is a replica of the machine and process and thus offer a very high accuracy (Rosen *et al*., 2015). It is a virtual representation of the actual physical component, product or system that includes more or less all information that mirrors its state and behaviour (Karanjkar *et al*., 2018). Digital Twins enable the processing of the machine's behaviour and the consequences of interaction with their environment (Qi and Tao, 2018; Tao *et al*., 2017).

Further advancements using AI might introduce self-tuning simulations that can react to changes by comparing past data with the simulation results and reach a very high degree of similarity (Badakhshan and Ball, 2022). This will be essential in contextualising data to understand consequences (Simons *et al*., 2017). The largest investment during the implementation phase of traditional Six Sigma projects is the development of new or adjusted processes that must be tested using the Design of Experiments (DOE) technique (Kelton, 1999). In a process that depends on many variables, it is difficult to achieve optimal conditions with the limited resources available without disrupting the manufacturing process. Therefore, accurate simulations that replicate the real system avoid the need for the required time and financial investment while being able to achieve a higher degree of refinement to achieve superior system optimisation (Montevechi *et al*., 2007). Also, instead of the conventional DOE, the 'retrospective DOE data mining' can be utilised, which can detect potential experimental designs from the huge amount of data and then draw out beneficial and meaningful information from alternative experimental designs (Chien *et al*., 2014.). After reiterating the simulation several times until a desirable outcome is achieved, the potential improvements of the KPIs can be analysed. Finally, risk and cost-benefit analyses are conducted to see if the changes are worth the trouble and have a low possibility of failing or causing other problems. If this is not positive with the proposed solution, further DOEs will be simulated until a satisfactory solution is achieved. The output of the *Simulation* phase is the list of optimised solutions that can be implemented through the next phase. Figure 5 shows the processes included in the adjusted Simulation phase along with the required technologies.

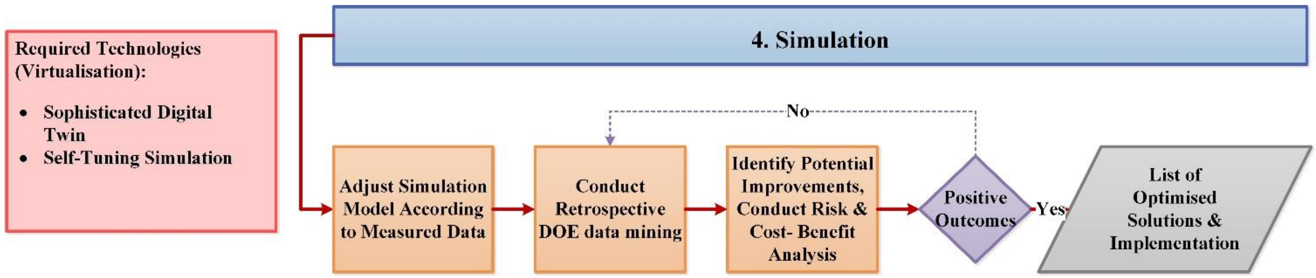

Figure 5. Illustrates the contents of the simulation phase, including its required technologies, processes, and output.

2.5 Enhancement Phase

As given in Figure 6, the last phase in the DMAISE cycle is the implementation of the proposed changes that result in the enhancement of the process. Up to this point, the simulation results have digitally determined the variables that need a change in the process. Here, a fully integrated CPS, a Self-adjusting System, is required to make decisions on its own with enough redundancy to be considered reliable and safe. It can adjust itself autonomously using actuators according to commands from the supervisory system. Another option for this might be using autonomous robots that can move freely and can learn new skills. Traditional robots require tedious programming to achieve this level of accuracy and have limited capabilities when working with humans (i.e., high safety precautions). New developments in visual and tactile systems will enable autonomous and collaborative robots to overcome these barriers (Bahrin *et al*., 2016). Subsequently, newly generated data needs to be compared with simulation data constantly and checked the similarity. If there is a higher degree of variance than expected (for example > 1%), the simulation model should be adjusted accordingly to represent the system after the changes, and the process of DOEs will be repeated. The final stage in this phase is the documentation of the manufacturing process versions with the implemented changes, deviations and remaining information that might be useful in the future.

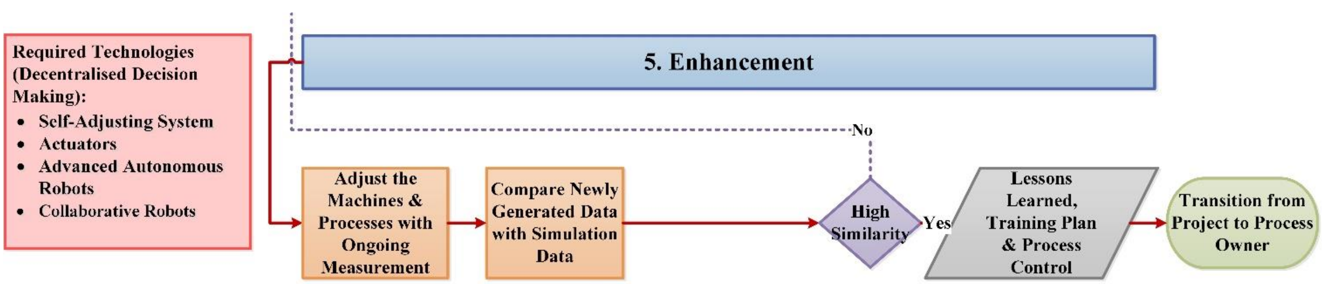

Figure 6. Illustrates the contents of the enhancement phase, including its required technologies, processes, and output.

All of these phases will still have to be done in the given sequence. However, the goal for the speed of recognising changes and implementing improvements is to reach real-time adjustments and thus improve competitiveness and flexibility to a level that is not possible today. The final DMAISE proposed cycle presented in Figure 7 includes step-by-step instructions on how to detect and eradicate inefficiency using the latest technologies.

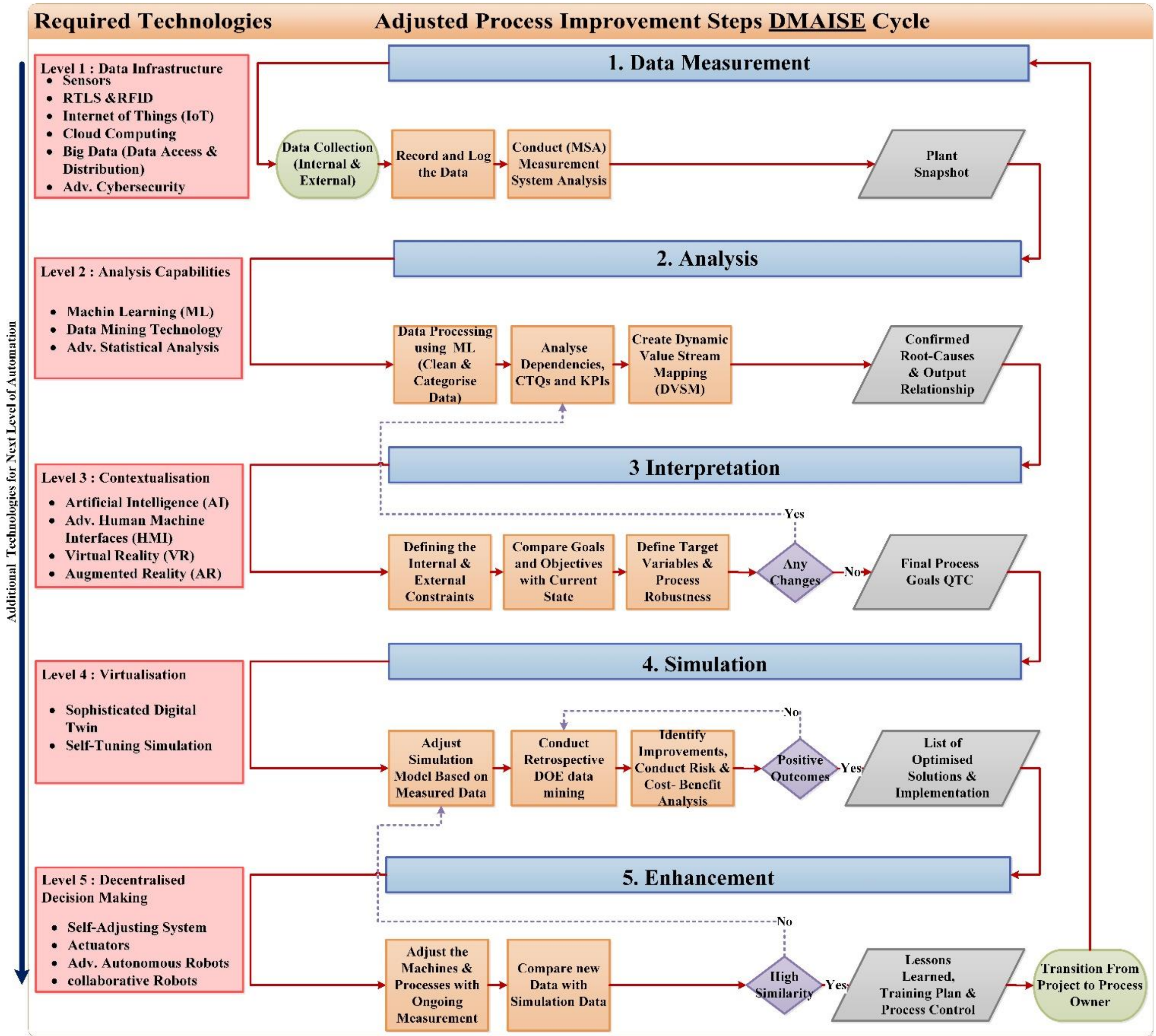

Figure 7. Illustrates the contents of the DMAISE cycle, including its phases, required technologies, processes and output of each phase.

3. VALIDATION OF THE PROPOSED DMAISE CYCLE

An empirical research study using a questionnaire survey was utilised in this paper to collect the required data and validate the proposed cycle. The questionnaire was designed for data collection purposes from academics and industrialists who were recognised and selected carefully by the research team as professional experts in this research area. The questionnaire was divided into two sections. The first section consisted of items related to the respondent's background. The second section of the questionnaire consisted of items related to evaluating the suitability of the proposed Six Sigma DMAISE cycle within Industry 4.0.

3.1 Data Collection

Data was collected through an electronic survey. A total of 70 questionnaires were sent out to professional experts, and thereby, 53 responses were received in the allotted time. The response rate (i.e., 76%) is considered to be quite high and acceptable (Saunders *et al*., 2009; Khamkham, 2017). The collected data were reviewed for completeness and correctness, and no significant errors were found. Therefore, the data were loaded into SPSS 24 software, and subsequently, several descriptive statistical analyses were conducted. Next, the applicable statistical analysis was performed to check the reliability and validity of the proposed DMAISE cycle. The details of the participant's profiles are presented in Table 1:

- This table shows that from the total respondents who returned the filled questionnaire, 30% were Quality Engineers, followed by Academics who are experts in Six Sigma implementation in the manufacturing environment, and Quality Managers with 19% each. The percentage of participants certified as green/black belt was 11%, and Directors, Project Leaders, and Quality Coordinators were recorded as 9%, 8%, and 4%, respectively.
- Moreover, 45% of the respondents have over ten years of work experience, 60% of the respondents have work experience of fewer than five years, and just 12% were between 6 and 10 years of experience.
- Table 1 also demonstrates the classification of the participants' sectors, where 28% of the respondents belonged to the Automotive sector, 24% were from the Aerospace sector, and 19 % belonged to higher education. The remaining 29% were others, including the Chemical, Customer goods, Electronics, Energy and Materials industries.
- Finally, as shown in Table 1, the majority of the 53 analysed participants worked at large companies with more than 1,000 employees (55%), followed by 28% working for a firm size of 1-249 employees and 17% from a firm size of 250-999 employees.

Table 1. Participants' profiles

Characteristics		Percentage (%)
Job title	Quality Engineers	30
	Academics	19
	Quality Managers	19
	Green/Black Belts	11
	Directors,	9
	Project Leaders	8
	Quality Coordinators	4
Work experience (in years)	0-5	43
	6-10	12
	+10	45
Industrial sectors	Automotive	28
	Aerospace	24
	Chemical & Pharma	6
	Consumer Goods	4
	Education	19
	Electronics	6
	Energy	7
	Materials	6
Firm size (number of employees)	1-249	28
	250-999	17
	+1000	55

3.2 Reliability and Validity Analysis

In this study, Cronbach's Alpha was used to measure the internal consistency of the instruments used to evaluate the proposed cycle. Typically, Cronbach's Alpha should be greater than 0.7 to consider that the items being measured are consistent and reliable (Field, 2013; Khamkham, 2017). Therefore, the test was employed for the following seven items to check both the consistency of the questionnaire and also how these items are closely related to the proposed DMAISE cycle:

a) the evaluation of the Required Technologies (RT),
b) the evaluation of the Proposed New Phases (PNP),
c) the evaluation of the content of the Data Management Phase (DMP),
d) the evaluation of the content of the Analysis Phase (AP),
e) the evaluation of the content of the Interpretation Phase (IP),
f) the evaluation of the content of the Simulation Phase (SP), and finally
g) the evaluation of the content of the Enhancement Phase (EP).

The results in Table 2 demonstrate that the coefficient alpha is 0.848, and the standardised item alpha is 0.847, which is greater than 0.7. Thus, all the items are consistent and reliable.

Table 2. Reliability test

Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	No of Items
.848	.847	7

In this study, three different types of validity tests were employed, including content validity, construct validity and criterion-related validity. In this research, the items of the questionnaire that have been used to evaluate DMAISE cycles and the 20 technologies associated with the DMAISE cycle have content validity since they were derived from an extensive review of the literature (Flick, 2018; Khamkham, 2017). In addition, Chi-Square goodness of fit was carried out to evaluate the construct validity of items that have been used for evaluating the proposed DMAIS cycle. Additionally, Exploratory Factor Analysis (EFA) was employed to extract the new factor structure and examine the construct and criterion validity of the items that have been used to evaluate the associated technologies of the proposed cycle.

3.2.1 Chi-Square Goodness of Fit Test

Chi-square goodness of fit was used to check the validity of the proposition items that were used to evaluate the proposed DMAISE cycle to ensure that the items measured what was supposed to be measured. Chi-square goodness of fit is used to measure to what extent the observed values are statistically significantly different from the expected values (Flick, 2018; Khamkham, 2017); the corresponding *P value* is significant if the *P value* is ≤ 0.05 (Bryman and Cramer, 2005). Therefore, the results in Table 3 illustrate that the *P-value* (i.e., Asymp. Sig) is less than 0.05 for all the items used to evaluate the proposed DMAISE cycle. This means that the results are significantly different from the actual observed values and expected values of all the considered items used to evaluate the proposed cycle. That can also be an indication of the possibility of publishing the results and generalising from the current research sample to the entire population (Balck, 2011; Alzuabi, 2015; Khamkham, 2017).

Table 3. Test Statistics

	Evaluation of the RT	Evaluation of the PNP	Evaluation of the DMP	Evaluation of the AP	Evaluation of the IP	Evaluation of the SP	Evaluation of the EP
Chi-Square	29.170[a]	24.642[a]	47.283[a]	40.491[a]	37.094[a]	30.302[a]	35.774[a]
df	4	4	4	4	4	4	4
Asymp. Sig.	.000	.000	.000	.000	.000	.000	.000

3.2.2 EFA Test

EFA was undertaken to identify the relationship (i.e., correlation) between the associated technology of the DMAISE cycle and DMAISE phases, determining the total number of latent factors represented on the survey and thus confirming the construct validity. Latent factors refer to the items of the questionnaire that have been used to evaluate the importance of 20 associated technologies with respect to the DMAISE cycle.

Construct validity is an effective technique for checking the unifactoriality of each factor (Thompson and Daniel, 1996; Khamkham, 2017). It is a measurement technique to examine whether the instrument's scales act like the measured attributes. Therefore, to identify the construct validity, the associated technologies must be evaluated by EFA. This is a crucial test used to measure the construct validity of each associated technology and determine the instrument's appropriateness (Pallant, 2010; Khamkham, 2017). Field (2013) stated that one of the main usages of factor analysis is to measure and understand the structure of the latent factors. Additionally, Williams *et al*. (2012) and Khamkham (2017) expressed that EFA is a statistical technique that describes the variability among observed correlated variables to explore and verify a set of correlation coefficients in three steps, namely, reducing a large number of variables into a smaller number, establish underlying dimensions between the measured variables and latent construct and hence provide construct validity evidence for self-reporting scales.

The EFA was undertaken with the use of SPSS 24 through the data-reduction factor analysis method to examine the construct validity of each associated technology of the DMAISE cycle in this analysis. The more variation explained by the factors resulting from factor analysis, the more powerful the instrument measures what is supposed to be measured (Mallak *et al*.,1997; Khamkham, 2017). Moreover, the Principal Component Analysis (PCA) method was employed to extract the factors. The PCA is a vital extraction method used in the literature to produce scale unifactoriality or unidimensionality (Williams *et al*., 2012; Khamkham, 2017).

However, Khamkham (2017) claimed that a sample size of more than 100 is required to carry out a good factor analysis, 'many arbitrary ''rules of thumb'' exist that specify the required number of cases, but there is no absolute scientific answer to this issue' (Wong and Aspinwall 2005, 71). Thus, the authors believe that performing factor analysis was better than not performing any to indicate the construct validity.

The purpose of extraction is to reduce many items into factors (Williams *et al*., 2012; Khamkham, 2017). To attain scale dimensionality and simplify the factor solution, ideally, multi-procedures should be used to analyse factor analysis (Thompson and Danial, 1996; Khamkham, 2017). In this regard, the most common procedures used by researchers to produce unidimensionality are:

- *Factorability test:* To check the appropriateness of data for obtaining factor analysis, the Kaiser-Meyer-Olkin test (KMO) is used to assess the suitability of the data set for factor analysis. This test is calculated based on the correlation matrix, where the higher the correlation among the variables, the more suitable of data for performing factor analysis test (Field, 2013). Moreover, Barlett's test of sphericity is used to check if the data have equal variation among the variables to ensure that there is redundancy between observed variables. Therefore, KMO with a value greater than 0.6 is satisfactory for factor analysis, whereas Barlett's test of sphericity should be significant and P-value ≤ 0.05 (Williams *et al*., 2012; Khamkham, 2017).
- *Factor extraction:* The PCA method with the Eigenvalue method is a vital method to identify the retained factors. The mathematical formula for calculating factors from the covariance matrix is taken from Anton and Rorres (2013 $Ax = \lambda x$, Where; λ = Eigenvalue and A = the covariance matrix. Any Eigenvalue with a value greater than (1.00) is considered to be acceptable and can be returned (Williams *et al*., 2012; Khamkham, 2017).
- *Factor rotation:* The Direct Oblimin technique is a method used for producing more correlated factors; the test provides patterns of loading in a manner that is easier to interpret (Williams *et al*., 2012; Khamkham, 2017). In this regard, if the factor loading is greater than 0.3, is considered to be a minimal level, greater than 0.4 is moderate and highly significant if more than 0.5 (Hair *et al*., 2006).

Hence, the first step is to examine the suitability of the data for factor analysis. The results in Table 4 demonstrated that KMO is 0.775, and the Sphericity test is significant. The KMO with a value greater than 0.6 is adequate for factor analysis, whereas Barlett's test of sphericity should be significant and P-value ≤ 0.05 (Williams *et al*., 2012; Khamkham, 2017).

Table 4. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.775
Bartlett's Test of Sphericity	Approx. Chi-Square	500.385
	Df	190
	Sig.	.000

Second, in factor extraction, the results of the primary solution obtained from the first trial were fairly unsatisfactory, where the results of PCA extracted five Latent factors with an Eigenvalue exceeding 1.00 (Williams *et al*., 2012; Khamkham, 2017). However, the results of the component matrix in Table 5 showed that most of the items loaded pretty strongly on only the first factor with a correlation value of more than 0.3, whereas most of the items loaded on the other factors are very weak and part of them are loaded negatively, which is resulted to retain only one factor for the next extraction run to aid the interpretation the view supported by (Pallant, 2010). Therefore, as can be seen from the results in Table 6, for the second run is extracted one latent factor that is eligible for being interpreted and labelled in a further step. Since only one factor is retained, factor rotation cannot be performed, and components matrix correlation can be used to interpret the structure of the latent factor obtained (Pallant, 2010; Khamkham, 2017). Hence, the results from the component matrix shown in Table 5 revealed that the entire items of the associated technologies are strongly correlated with the latent factor, with correlation values ranging from 0.782 to 0.333. As it can be seen that five items are highly correlated with the latent factor, which are IoT, self-adjusting system, self-tuning simulation, Advanced Autonomous Robots and Advanced Cybersecurity, with a correlation value of more than 0.7. These items are considered the most vital technologies of Industry 4.0 associated with the DMAISE improvement cycle. Consequently, the latent factor obtained can be labelled as the most significant key driver for implementing the DMAISE cycle within Industry 4.0, where the latent factor with its correlated items has a significant impact on the implementation process of the DMAISE cycle developed in this study. Moreover, the latent factor explained 38.059% of the variances (see Table 6).

Therefore, the survey instruments of the DMAISE cycle's associated technologies are validated since the entire items correlated strongly with one latent factor with a high loading greater than 0.33 as well as the internal consistency of the latent factor was tested and found to be 0.94, which is greater than 0.7 (See Table 7). Therefore, the associated technologies of the DMAISE cycle are statistically considered significant and reliable.

Table 5. Components matrix

Evaluation of the important technologies of the DMAISE cycle	Component				
	1	2	3	4	5
Sensors	.336	.171	.132	.685	.222
RFID	.627	.301	.230	.034	.120
Internet of Things (IoT)	.782	.110	.055	.295	.199
Cloud Computing	.608	.259	.361	.221	.178
Big Data (Data Access & Distribution)	.635	.174	.330	.274	.233
Advanced Cybersecurity	.699	.115	.086	.232	.156
Advanced Statistical Analysis	.333	.332	.519	.166	.368
Data Mining	.444	.394	.153	.034	.474
Machine Learning (ML)	.648	.331	.149	.205	.071
Actuators	.501	.192	.061	.059	.472
Artificial Intelligence (AI)	.654	.255	.127	.345	.138
Advanced Human-Machine Interface	.492	.065	.522	.234	.303
Augmented Reality (AR)	.590	.595	.032	.118	.024
Virtual Reality (VR)	.632	.557	.295	.018	.081
RTLS	.662	.385	.064	.089	.017
Sophisticated Digital Twin	.616	.211	.308	.238	.053
Self-tuning Simulation	.740	.064	.172	.180	.232
Advanced Autonomous Robots	.704	.335	.245	.043	.075
Self-adjusting System	.762	.238	.016	.256	.013
Collaborative robots	.627	.038	.183	.030	.263

Extraction Method: Principal Component Analysis.

a. 5 components extracted (i.e., Latent factors extracted).

Table 6. Factors extraction for the retained factor

Total Variance Explained						
Latent factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	7.612	38.059	38.059	7.612	38.059	38.059
2	1.755	8.776	46.835			
3	1.237	6.185	53.020			
4	1.162	5.811	58.832			
5	1.052	5.261	64.092			
6	.948	4.740	68.833			
7	.913	4.565	73.398			
8	.822	4.108	77.506			
9	.727	3.634	81.140			
10	.629	3.146	84.285			
11	.539	2.695	86.980			
12	.516	2.580	89.561			
13	.476	2.381	91.942			
14	.413	2.063	94.005			
15	.352	1.760	95.765			
16	.243	1.216	96.981			
17	.199	.994	97.975			
18	.180	.900	98.875			
19	.140	.702	99.577			
20	.085	.423	100.000			

Extraction Method: Principal Component Analysis

Table 7. Component matrix of the factor retained.

	Component Latent factor
	1
Cronbach alpha test of the latent factor	**.94**
Internet of Things (IoT)	.782
Self-adjusting System	.762
Self-tuning Simulation	.740
Advanced Autonomous Robots	.704
Advanced Cybersecurity	.699
RTLS	.662
Artificial Intelligence (AI)	.654
Machine Learning (ML)	.648
Big Data (Data Access & Distribution)	.635
Virtual Reality (VR)	.632
Collaborative robots	.627
RFID	.627
Sophisticated Digital Twin	.616
Cloud Computing	.608
Augmented Reality (AR)	.590
Actuators	.501
Advanced Human-Machine Interface	.492
Data Mining Technology	.444
Sensors	.336
Advanced Statistical Analysis	.333

Extraction Method: Principal Component Analysis.
a. 1 components extracted (i.e., latent factor extracted)

4. CONCLUSION AND DISCUSSION

In the current competitive world, manufacturing companies face diverse competition characterised by changing customer expectations, intense competition, globalisation, financial crisis, and economic downturn. Under these challenging environments, for companies to be competitive, they must constantly adapt to the latest technologies and processes to maintain the sustainability of the process. I4.0 is the latest advancement in the industrial process, which has been presented as a solution to ensure the productive sector's success in the digital era but must be aligned with organisational process improvement to guarantee such sustainability. Hence, the focus of this research was on the Six Sigma DMAIC methodology to introduce a new quality improvement cycle toward Industry 4.0.

4.1 Contribution to the Body of Knowledge

To the best of our knowledge, this is the first paper that proposed a new Six Sigma improvement cycle within Industry 4.0 to incorporate the Six Sigma DMAIC advantages and Industry 4.0 capabilities (e.g., technologies) in a single framework. In this paper, the impact of the digital era on the implementation of the Six Sigma DMAIC cycle was studied and led to the development of a new implementation cycle called the **'DMAISE Cycle'.**

The DMAISE cycle consists of five main phases, which are *Data Measurement*, *Analysis*, *Interpretation*, *Simulation* and *Enhancement*. The process steps and outcomes, along with associated technologies, have been defined in detail. A questionnaire was developed to collect opinions from practitioners, researchers and managers who are experts in implementing Six Sigma in their organisations to validate the proposed cycle.

4.2 Contribution to Practice

Since 2011, when Industry 4.0, the newest industrial revolution, was announced in Hannover, this movement has started and expanded from some theoretical concepts to real-world applications worldwide. The considerable amount of data generated from Industry 4.0 is essential for the Six Sigma implementation as it is a data-driven approach to continuous improvement. Hence, there is an identified need for the integration between both Six Sigma and Industry 4.0 to enable practitioners to collect and analyse data in real-time and propose solutions to cope with uncertainties in the workplace. The proposed DMAISE cycle not only can be considered a viable quality improvement methodology for the new challenges that arise with

Industry 4.0 and its technologies but also is valuable for industrial organisations and can lead to improving the quality system and attaining high operation performance at a faster rate to cope with the amount of data generated in today's digital era.

4.3 Impact on Society and Education

Saad *et al.* (2023) stated that: "society doesn't acquire the required skills to cope with the application of digital technologies in Six Sigma organisations. There is a two-dimensional problem in this regard: neither the Six Sigma practitioners are fully aware of digital technologies and data analytics, nor are the digital professionals entirely knowledgeable about the Six Sigma principles. This proves the need to update Six Sigma practitioners and digital professionals on Six Sigma and I4.0".
It is the duty of universities to provide specialised courses to cover Six Sigma and the implication of the digital era on the implementation of Six Sigma in today's environment. The research team of this paper have already started this mission within the community.

4.4 Limitations and Future Research

As with any study, this research work has some shortcomings. However, these shortcomings can be a route and map for future research. It would be interesting and necessary to investigate whether the traditional Six Sigma tools can still be used in the new cycle or if there is a need to identify new tools and techniques that can be utilised in the proposed cycle. In addition, the DMAISE cycle is now at a stage of development that requires detailed industrial evaluation to identify its risks, opportunities and critical success factors with regard to the industrial performance of enterprises before being tested in the real environment.

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