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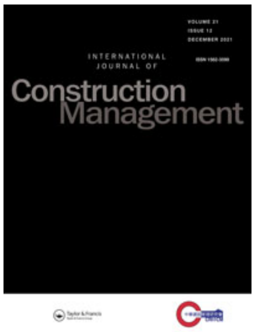

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Managing quality control systems in intelligence production and manufacturing in contemporary time

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ABSTRACT

In contemporary time, the production arena has become an interesting scene with introduction of innovations that is changing the climate of production technology. The innovation comes in the form of smart technique of production for an enhanced productivity. Which is termed intelligence manufacturing or production. Intelligence manufacturing has led to enhance productivity in manufacturing sector in recent time on account of 4th industrial revolution. Intelligent manufacturing (IM) involves the use of sophisticated and advanced analytics, sensor application in robotics and internet based connections to things popularly known as IoT. This study was centered on application of intelligent manufacturing in industrial productivity and cost/time wastage. Purposive sampling method was adopted in this study, random sampling survey methods was used to pick samples for collation of **responses from production managers of manufacturing companies at** the study area (Lagos state, Nigeria). Population frame of 100 product manufacturing companies was adopted, out of which 73 respondents that constitute production managers and supervisors were selected using random sampling technique. The study censored the opinion and view of professionals such as managers (production), production supervisors on calibrated. The study highlighted emerging areas of application of quality monitoring system in intelligent manufacturing to include advanced analytical tools and censored based applications such as robotics applications used in design and product calibration, virtual and augmented reality application that simulates real situation using virtual approach, machine learning, expert systems (AI), block chain technology, drones for real time supervision of production process.

KEYWORDS

Internet of things; calibration; intelligent system; merging; dynamics

Introduction

One of the major factors that influences intelligent manufacturing system is managing quality control system. Quality control system has received worldwide acceptance in view of need for an enhanced productivity. In quality assurance process of industrial manufacturing quality of design, and production process assist in process monitoring. In the manufacturing parlance quality control concept is dynamic in interpretation, some school of thought believes that quality definition is subjective in nature. The quality of a product may be the objective of manufacturing or quality of the production process. Therefore, there should be protocol that should be attached to either of the quality objectives as mentioned. In Abdul Rasid et al. (2014) the study submitted that there are philosophical thoughts that backs up quality concepts, the philosophical point explained quality from the subjective point of customer satisfying the customers. Therefore, in the school of thought depends solely on conditioning production objectives based on the customers' requirement. Similarly, in a study carried out by Adedayo et al. (2006) and Skrop et al. (2018) a study was carried out on smart manufacturing, manufacturing intelligence and advanced dynamic performance computation. The system establishes quality control system in intelligence manufacturing. The smart manufacturing entails setting units of achievable tasks that could be easily achieved. Different stages of quality could be easily controlled. For instance, in construction, cost could be controlled at different stages of construction work with emphasis on cost, time and materials, therefore effective quality control system would entails setting standards for monitoring, control and implementation of three axioms in production management which include time, cost and process. Also, Skrop et al. (2018) emphasizes on the importance of quality control system in manufacturing in producing quality output. In achieving quality product and process techniques and procedure of achieving quality matters. Lekan et al. (2021) emphasizes the importance of quality control system with the aid of state of art techniques and tools. The tools are noted for high quality results with consistent output. In the real sense of manufacturing, researches has indicated rise in the adaptation of state of art tools and techniques in industrial production and manufacturing since the tools and techniques being used currently need changing, therefore the need for paradigm shift in automation in the manufacturing and production process of industries. The need for the introduction of automated industrial system was stressed in Lekan et al. (2021), Mukherjee et al. (2016) and Bao Sasha 2018 and which has led to the adaptation of industrial revolution 4.0. The advent of i4.0has warranted the research into quality assurance issues about intelligent manufacturing. It was viewed by researchers such as Arijit, Abhijit, Sujit (2016) and Bao Sasha 2018 that control of processes right from design to product calibration and packing contributes to the final

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form of quality essence obtainable from a product, which are now better monitored through an improved system referred to as intelligent quality control process as presented in part of sections in this study. In monitoring quality control system in intelligent manufacturing, industrial revolution 4.0 that allows the use of sensor-based application was stressed. There are systems that has been calibrated with state of art sensors and control points which facilitates on the site, real time or concurrent monitoring of quality process during manufacturing, they are regarded as smart technology, smart adaptations, smart application with some even equipped with Artificial intelligence adaptations. The application has been changing rules of operations in manufacturing industry over the world since it came in the form of disruptive adaptations, therefore this study attempted to carry out an exploratory research on the disruptive adaptation interventions of smart technology of industry 4.0 in enhancing quality control system management in achieving intelligent or smart industrial manufacturing process.

Aim and objectives

In the context of this study, the study aims at exploring the quality control system in intelligent manufacturing with a view to identifying the disruptive applications in-use in achieving quality production in contemporary time to make available system and techniques that would enhance industrial production and manufacturing.

The following objectives are set for the study:

i. To study and profile the state of adaptability of quality system monitoring in smart manufacturing
ii. To investigate problems and challenges being encountered in quality control monitoring in smart manufacturing
iii. To explore potential disruption tools for product quality enhancement in intelligent manufacturing process
iv. To profile critical success enhancers of quality control monitoring in smart manufacturing
v. To Profile Critical Success Factors Influencing achieving Effective Intelligent Manufacturing
vi. To Study strategy for the deployment of Disruptive Innovation in Intelligent Manufacturing System

Literature review

Relevant discuss about the concepts presented in the title of the work is presented in this literature review sections, the component is a blend of concepts harvested from the objectives and research questions. The study carried out on intelligent manufacturing advancement as relates to quality control monitoring system in Beata, Edwin (2015), followed up on the application of artificial intelligence in in solving logistic problem in industrial manufacturing, the study centered on the state of art of application in intelligence manufacturing, the state of art of application that has been changing games include but not limited to the following: application of reinforced learning in industrial manufacturing, cyber-physical system, Internet of things (IoT), semi -conductor, manufacturing and generation of demand forecast models. The components listed above has been a major driver in intelligence manufacturing and additive manufacturing in contemporary time as demonstrated in Béla, Péter, Péter, Róbert. In the light of the above, developed framework for a cyber-additive manufacturing system using artificial neural network. The network was used to design monitoring system for different manufacturing techniques. However, Bicum and Theodor developed a system for providing improved product quality system using real time monitoring and additive manufacturing. The techniques used by the authors enables application of big data and provides clue to practical importance to of additive manufacturing in intelligent manufacturing presented in this study. The feature of that rely on sensor data for quality control measurement. The view that the authors presented in their study was adjudged to be reliable, consistent, stable and robust to be able to enable machine learning to be used to achieve high level of quality detection in manufacturing process. Similarly, correct decision making is one of the essential factors for effective quality control system in product manufacturing and industrial production, focusing on an optimal alternative in manufacturing decision. In this case, different algorithms are often deployed, for instance in Bicum and Theodor. The Béla, Péter, Péter, Róbert earlier reviewed sensor based algorithm were used with the aid of intelligence system. In Bierma and Waterstraat (2001), however, Bayesian logic was used, relying on the strength of fussy logic in Bayesian network environment ion intelligence system design. Maxim programming model was used, to develop a Bayesian network-based system. The system was not sensor based as in the case of Bicum and Theodor. The network was good in decision making in maintenance operation, especially when multi Pareto optimal policy is the focus. Of new paradigm. Furthermore, smart manufacturing and intelligent manufacturing are sin-qua-none as demonstrated in this study, this was corroborated by the presentation in Bierma and Waterstraat (2001). The study presented by Bierma and Waterstraat (2001) argued on the meaning and etymological composition of intelligent manufacturing thereby shared similarity with the view presented in this study about intelligent manufacturing at the introductory section. The similarity borders about the connection point of intelligent manufacturing being sensor-based. In the context of this study then, the future of product design is in the application of smart system which with up to date technology of sensor application. Bierma and Waterstraat (2001). Further consolidated the global acceptance of intelligent manufacturing to be having global dimension stating that the countries with the highest application to include the following: United States of America, Germany, Korea, Finland, France, Japan, Sweden, India and Spain. In a related study to the above, Bierma and Waterstraat (2001), Bourne and Fox (1984). Bourne and Fox (1984). presented detail of IM system and areas in quality control in intelligent manufacturing as to include: advanced manufacturing, cyber-physical production, cloud manufacturing, digital manufacturing, sustainable manufacturing, flexible manufacturing, holonic manufacturing, CIM, agile manufacturing, reconfigurable manufacturing, network manufacturing, IoT-based manufacturing, E-manufacturing, lean manufacturing and social manufacturing which this submission follows closely. However, factors that affects quality control system in intelligent manufacturing was listed in some relevant materials cited in this study, for instance, Arijit, Abhijit, Sujit (2016) suggested digital divide and scarcity of technology, Ahmad Adnan Al-Tit (2017) mentioned digital divide as a major factor while other suggested the following reasons in the following order: Arijit, Abhijit, Sujit (2016) high cost of component, language barrier and illiteracy, Bao Sasha (2018) world order policy on software business, Beata, Edwin (2015 resistance to acceptance of ICT, Bao Sasha 2018 cultural and economic divide, while Bicum and Theodor suggested knowledge and skill transfer challenge, cybercrime, menace of pirates and international and intercontinental cyber terrorism. The following literary content has made key contribution in addition to Bicum and Theodor already discussed earlier, other key literary items that has advanced the body of knowledge such as Brüggemann and Bremer (2012); Chang, Muhhamed, Biswajit and Mohammed (2018); Choy et al. (2004); Colledani et al. (2014) and Darko and Heimo (2019). The study has no shortcoming but rather enriched the discuss on intelligent manufacturing and quality system control. Issues presented in the study addressed the specific objectives approved for their studies and are apt to the title of the research.

Quality control managing production process in industrial production and manufacturing

In contemporary time quality of a product is counted as one of the requirements in determining the worth of a product. It is also a believe that quality of a product is determined right from the product design to the time of product manufacturing. It implies that quality of a product is a collective contribution of designers' input, customer request and prescription and the production crew input. The need to meet customers and end-users demand expectation has led to search for improve method of approach in product calibration, design and manufacturing, which led to the emergence of application of approached in industry revolution and quality revolution. This approach led to emergence of industrial manufacturing digital manufacturing. Quality revolution (Quality 4.0) involves application of automation in quality design, monitoring and production. In advanced countries of the world like those in Asia, Korean, America, Germany and France among others, automation methods are being employed to carry out quality monitoring and control. Product features are designed bade on product and process simulation before the actual production through application of robotics and Artificial intelligence (AI). In industrial quality revolution (Q4.0) as presented in Darko and Heimo (2019), Davis et al. (2012), Delloite (2016), ENQA (2019) and Felício et al. (2014). Artificial intelligence approach was used in product description, calibration and development through a pre-calibrated featured for precision manufacturing. In Korean peninsula and China, cartographic instruments are enabled with sensor-based statistical analytical machine that tend to picture the observed trend in quality control process during manufacturing process. For instance, as presented in Bernaden, Sarh (2012) the following Japanese technology uses Artificial intelligence aided methods to generate quality output, the system includes Ishikhaw, flow algorithm, correlation analysis diagram, flow system among others that are sensor based for precision. Similarly, the advent of Industry4.0and Construction4.0 has greatly enhanced output quality through creating intensive system reliability. The system reliability enables product precision prediction and accomplishment which enables systems and process quality reliability, as supported in Davis et al. (2012), Delloite (2016), ENQA (2019) and Felício et al. (2014).

Industrial revolution [Industry4.0] intervention in the disruptions of quality control system

The adventure of Industry 4.0 in the product manufacturing industries has been trending. In industrial manufacturing, automation of production process is a great hallmark. Automation of the process has been a game changer which has enabled the manufacturing terrain in industries to change from primitive machine application to automated system with intelligence enabled sensors. According to Felício et al. (2014), Fernández-Pérez et al. (2012) and Feigenbaum (1991) submitted that applications that are sensor based are now in use in companies in quality manufacturing, some of the applications includes data analytics, Internet-of-things enabled application, machine learning among others. Industrial revolution of I4.0, is set to revolutionize the manufacturing process, through quality improvement and standard reformation. Therefore, according to the submissions in Fox et al. (1983), Gubán and Kása (2011), Guo and Zhang (2010) Gilchrist (2016), and Safty (2020) there are number of applications that could be described as disruption of status quoin industrial manufacturing that spans product design to product marketing? Some of the applications includes that following: Internet of things applications, smart sensor based design and calibration applications, industrial mechatronics, smart site managers, cloud storage and cloud data storage, Artificial intelligence {AI} applications, Robotics design and application among other disruptive applications.

Challenges in quality control system

There are a lot of challenges associated with quality management in intelligence manufacturing in quality control system. In a study carried out by Haq et al. (2010) and Hairulliza, Ruzzakiah, and Ganessan (2011); it was stated that the transformational changes associated with industrial 4.0 and digital development has brought different changes in quality management landscape transformation. In industrial manufacturing, precision is of essence, precision manufacturing in industrial manufacturing entails the use of precision instrument in design, calibration, measurement and product manufacturing process. The precision instruments are the instruments that are equipped with sensors that are sensitive to pick faults and diagnose faults at the same time. Some of such equipment as documented in some studies remotely such as Lekan et al. (2021), Arijit, Abhijit, Sujit (2016) and precisely in Chang, Muhhamed, Biswajit and Mohammed (2018) and Colledani et al. (2014). In Chang, Muhhamed, Biswajit and Mohammed (2018), sensor based application are described as intelligent tools of industrial manufacturing and production. Some of the tools assist in production forecast in solving forecasting challenges often associated with industrial manufacturing. Therefore, one of the challenges of quality control system is ability to adopt effective tools for production operations. Furthermore, the choice of production system also plays crucial role in achieving an effective flow system. In flow shop application as peculiar to Toyota production system, there should be adequate job and material resources flow, therefore an effective tools that could design and simulate the process adequately is highly needed, this toes the line of submissions as presented in Hirsch-Kreinsen (2014) and Hou et al. (2010). Similarly, the following challenges were identified in some previous studies such as ENQA (2019), Hirsch-Kreinsen (2014), Jasko et al. (2018) and Kagermann et al. (2013), they include improper management of flow of operations items, good and services by Hirsch-Kreinsen (2014) and Jasko et al. (2018), insufficient applications and manpower back-up by ENQA (2019), maintainability of machine component, inadequate planning Jasko et al. (2018) and menace of hackers Jasko et al. (2018) and Kagermann et al. (2013).

Methodology

Materials and methodology adopted to carry out the study was presented in this section. **Purposive sampling method was used in this study** while random sampling technique was used to pick the data samples. Structured **questionnaire designed in Likert scale was used** to gather data, Bourne and Fox (1984) [13], Brüggemann and Bremer (2012) and Choy et al. (2004).

Material and tools

Some materials were engaged and used for the purpose of generating data for research work presented in this study. With the aid of the Likert scale tools adopted agreement index and mean index was calculated for some groups of questions, the index is as described by the equation 1 below:

$$\text{Relative Agreement Index} = \sum \text{Wi/A x N} \qquad \text{Equ1}$$

Where RAI = Relative Agreement Index, Wi = Weighted Sum, A = The number of items on Likert scale of 1-5.

Summarily, Purposive sampling method was adopted in this study, random sampling survey methods was used to pick samples for collation of responses from respondents that constitutes managers that are involved in production (production manager) at the study area (Lagos state, Nigeria). Population frame of 100 product manufacturing companies was adopted, the population was derived from the office of Bureau of Statistics and Corporate affairs commission to get the detail of registered companies out of which the population frame of 100 was created and sample size of 80 respondents picked through random sampling technique. Eighty 80) respondent that constitute production managers and supervisors were selected using random sampling technique. The Statistical Package for Science and Social Science Students (SPSS) 24.0 software was used to analyze the data with Man-Whitney U Test kits, T-test kits, and Pearson's Rank correlation kits was adopted in data analysis. For the purpose of the study, eighty (80) questionnaires which represents seventy-three questionnaires was used for the study to officers like Managers for product production; officers in charge of process quality, Task supervisors and others. Different sizes of the company were surveyed in order to have an inclusive respondents and adaptive results, this allows for cross fertilization of ideas and opinion to be able to have a result that could be adoptable to all cadre of industrial segment. Besides, the focus is non-discriminatory application of results outcome (Table 1).

Discussion of findings and results

Characteristics of research respondents

Analysis of characteristics of the respondents was presented in Table 2. The data was extracted from the cross section of the respondents used for the research work. As presented in the table, category of respondents includes product production officer [PPO], product production manager [PPM], and quality control officer [QCO] and information communication technology manager [ICTM]. The analysis of the respondents' formation revealed that 31.5% of the respondents belong to product production officer category, thus ranked 1st, while product production manager and quality control manager constitute 27.4% respectively therefore ranked 2nd respectively. Information Communication-Technology Manager constitutes [ICTM] 13.70% and ranked 4th. The implication of the survey lies in even spread of relevant officers that controls the relevant operations in quality assurance and production management. The production managers are the operatives that implements the quality objectives and specification specified by the quality control managers, therefore being more that others in the line of production is in order, this toes the line of submissions in Bourne and Fox (1984), Colledani et al. (2014); Feigenbaum(1991) and Fox et al. (1983).

As presented in Table 3, academic and professional qualification of the respondents was stressed. The category of the respondents and their various academic and professional qualification was presented in Table 2. Qualification of the respondents cuts across the following cadre: Master of Science, Higher National Diploma, Professional Certificate and Bachelor of Science degree. Product Production Officer Crew [PPO] has the largest population of 25 operatives, this was followed with 24 operatives of Quality Control Manager, also 21 operatives of Product Production Manager [PPM]. Similarly, 21 Product production Manager and 13 Information Communication technology manager. The analysis reveals the skewedness of the operatives qualification towards the Trades certificates and Bachelor of science degree, the analysis indicates the knowledge background of all the cadre of operatives having minimum qualification of Bachelor of science and additional trade certification while a few had it up to master degree level. The breakdown above is supported in Gubán and Kása (2011), Guo and Zhang (2010), Gilchrist (2016) and Haq et al. (2010).

As presented in Table 4 below, in intelligent manufacturing there are many applications that has aided quality calibration, design and monitoring which has enhanced productivity. Some of the profiled quality system monitoring application in smart manufacturing include the following applications: Platform design and calibration platform, calibration platform with Sensor applications, platform design and monitoring technology, product process analytical system technology, operations research and technology, smart and Intelligent System for Sequencing, psychometric intelligent –based system, smart and Intelligent spindle system for quality assurance and monitoring, 3 D,4D and 5 D Design and Calibration System for quality monitoring. Some studies has described the contributions of some of the applications in intelligent manufacturing, for instance Hairulliza, Ruzzakiah and Ganessan (2011), Hirsch-Kreinsen (2014), Hou et al. (2010) and Jasko et al. (2018) described the sensor based application to enhance product manufacturing, product quality and speed of production. Also, Kagermann et al. (2013), Korenko et al. (2013) and Kučera et al. (2014) stress the impact of disruptive application enhanced product quality calibration and quality monitoring process. In Table 4, disruptive application that enables quality design and monitoring to be possible. For instance the top rated application is the Platform design and calibration platform which was rated 1st with relative agreement index [RAI] value 0.869, calibration platform with Sensor applications was ranked 2nd with RAI value of 0.786, platform design and monitoring technology with RAI 0.771 was ranked 3rd, while product process analytical system technology with 0.754 was ranked 4th Similarly, operations research and technology was ranked 5th, smart and Intelligent System for Sequencing, psychometric intelligent –based system with RAI 0.679 and 0.657 Finally, were ranked 6th and 7th respectively. Smart and Intelligent spindle system for quality assurance and monitoring, 3 D,4D and 5 D Design and Calibration System for quality monitoring were ranked least. The pattern above is supported by view in Hairulliza, Ruzzakiah, and Ganessan (2011), Hirsch-Kreinsen (2014), Jasko et al. (2018).

Table 1. Operationalization of research variables.

Research Parameters	Parameters Scale	Research Variables	Reference
Questions 1-6 Bio-data information, Work experience. Technique for Analysis: Mean, Frequency, Pearson ranking.	Ordinal, Numeric Likert-Scale	Types of managers, Respondent cadre, and managers	Delloite (2016); Felício et al. (2014).
Q7-15 To study and profile the state of adaptability of quality system monitoring in smart manufacturing Technique for Analysis: Chi-square analysis, Kendal-Tau technique and Mean index/Relative Agreement Index and Pearson ranking	Numeric and Likert-scale	Adaptability of quality system monitoring in smart manufacturing	Felício et al. (2014) and Davis et al. (2012).
Q16-25 To investigate problems and challenges being encountered in quality control monitoring in smart manufacturing. Technique for Analysis: Chi-square analysis, Kendal-Tau technique and Mean index/Relative Agreement Index and Pearson ranking Man-Whitney U Test.	Numeric and Likert-scale	Problems and challenges being encountered in quality control monitoring in smart manufacturing.	Delloite (2016)
Q26-33 To explore potential disruption tools for product quality enhancement in Intelligent manufacturing process. Technique for Analysis: Chi-square analysis, Kendal-Tau technique and Mean index/Relative Agreement Index and Pearson ranking Man-Whitney U Test	Numeric and Likert-scale	Potential disruption tools for product quality enhancement inIntelligent manufacturing	Delloite (2016) and Davis et al. (2012)
Q34-44 To profile critical success enhancers of quality control monitoring in smart manufacturing Technique for Analysis: Chi-square analysis, Kendal-Tau technique and Mean index/Relative Agreement Index and Pearson ranking	Numeric and Likert- Scale	Critical success enhancers of quality control monitoring in smart manufacturing	Felício et al. (2014) ,Fernández-Pérez et al. (2012) and Feigenbaum (1991).
Q45-54 Potential Disruption tools for product enhancement intelligent Manufacturing Technique for Analysis: Chi-square analysis, Kendal-Tau technique and Mean index/Relative Agreement Index and Pearson ranking	Numeric and Likert- Scale	Potential Disruption tools for product enhancement intelligent Manufacturing	Felício et al. (2014)
Q55-68 Strategy for the deployment of Disruptive Innovation in Intelligent Manufacturing System	Numeric and Likert- Scale	Strategy for the deployment of Disruptive Innovation in Intelligent Manufacturing System	Feigenbaum (1991)

Table 2. Characteristics of research respondents.

Class of Respondents	Counts/Frequency	Percentage (%)	Rank
Product Production Officer [PPO]	23	31.50	1st
Product Production Manager [PPM]	20	27.40	2nd
Quality Control Manager/Officer[QCO]	20	27.40	2nd
Information Communication-Technology Manager [ICTM]	10	13.70	4th
	73	100	

The state of adaptability of quality system monitoring in smart manufacturing

In Table 5, critical success enhancers of quality control monitoring in smart manufacturing was profiled. The factors are success nuggets that influences successful implementation of quality control monitoring in smart manufacturing. The presentation in Table 5 above toes the line of submissions in previous studies like Lekan et al. (2021); Colledani et al. (2014); Feigenbaum (1991); and Fox et al. (1983). The success parameters are as presented. Strategic Flow system monitoring and evaluation with RAI score of 0.873 was ranked 1st along-side, Automatic rectification and fault diagnostic system with RAI 0.873. Also, automatic design and calibration of quality control system with RAI scores 0.769 was ranked 2nd, Up-to-date data generation transfer and harvesting with RAI 0.754 was ranked 3rd. Similarly, Smart and effective cost of quality control process was score 0.754 and ranked 4th, while System feed-back and monitoring strategy with 0.732 was ranked 5th, and Effective Factors influencing Effectiveness of Quality Control Monitoring training of manpower and human resources of RAI 0.653 was ranked 6th. Consequently, ensuring man-machine system compatibility with RAI 0.623 was ranked 7th while Setting up of smart system maintenance for extending machine live was scored with RAI value 0.610 and ranked 8th. The breakdown above presented above is supported in Davis et al. (2012), Levin (2010) and Lichtblau et al. (2015). In order of scoring of the parameters, Strategic Flow system monitoring and evaluation and Automatic rectification and fault diagnostic system were ranked first out of the success factors. Setting up of strategic flow system for quality monitoring system, this is important for effective monitoring of quality of the product and process. Automation is very important in ensuring higher productivity in industrial manufacturing, therefore automation is highly essential for manufacturing success in intelligent manufacturing this could account for the ranking of the factors as first. In line with this, automatic design and calibration of quality control system can ensure an up-to-date data generation transfer and harvesting in quality control and monitoring. Similarly, in Delloite (2016) and Feigenbaum (1991) it was opined that smart and effective cost of quality control process has a determinant effect in ensuring feed-back and monitoring strategy while creating system feed-back and monitoring strategy would ensure remediation of any defect arising therefrom (Lekan et al. 2021; Colledani et al. 2014; Feigenbaum 1991; and Fox et al. 1983).

Profiling critical success enhancers of quality control monitoring in smart manufacturing

Statistical analysis was carried using the Mann-Whitney-U tools of independent T-test of Statistical Package for Social and Science Student [SPSS]. The outcome of the analysis **was presented in** Table 6. **The U-value of 24** was used at Probability Function P value at 0.05. From the analysis the **Z-score value is 0.00 while the P-value is 1.5 and 2.0**.Fromthe results of the analysis there is no **significant** difference on the respondent view as regards factors influencing effectiveness of quality control and monitoring system (Li et al. 2013; Felício et al. 2014; and Feigenbaum 1991).

Analysis of agreement level on factors influencing effectiveness of quality control monitoring

Statistical analysis was carried using the Mann-Whitney-U tools of independent T-test of Statistical Package for Social and Science Student [SPSS]. The outcome of the analysis **was presented in** Table 7. **The U-value of 24** was used at Probability Function P value at 0.05. From the analysis the Z-score value is 0.00 while **the P-value is 1.5 and 2.0**. From the results of the analysis there is no significant difference on the respondent view as regards factors influencing. The Chi-square analysis value is 0.261. There is no divergent of opinion on factors influencing Effectiveness of Quality Control Monitoring

Chi-square test results was presented in the Table 6 above. Statistical analytical tools such as Pearson's -T test and Student-T test were used to analyze the data obtained from the respondents. Test for equality of variance was conducted on the data so as to determine the extent of variation on the agreement of opinion among the respondents. The equality of variance test results was presented in Table 8. The outcome of the analysis indicated non-significant difference in the opinion of the respondents. The test was carried out at confidence interval of 95% resulting in probability (P) value of 0.05. The P-value was greater than 0.05. The outcome of the statistical value implies the rejection of Null-hypothesis that states that there is no variation in the satisfaction level of the respondents. This implies that the respondent has thorough understanding of the censored variables (Li et al. 2013; Holubek and Kostal 2012; and Elhoone et al. 2017).

Chi-square test results was presented in the Table 8 above. Statistical analytical tools such as Pearson's -T test and Student-T test were used to analyze the data obtained from the respondents. Test for equality of variance was conducted on the data so as to determine the extent of variation on the agreement of opinion among the respondents. The equality of variance test results was presented in Table 8. The outcome of the analysis indicated non-significant difference in the opinion of the respondents. The test was carried out at confidence interval of 95% resulting in probability (P) value of 0.05. The P-value was greater than 0.05. The outcome of the statistical value implies the rejection of Null-hypothesis that states that there is no variation in the satisfaction level of the respondents. This implies that the respondent has

Table 3. Academic and professional qualification of the respondents.

Qualification	PPO	QCM	PPM	ICTM
Master of Science	0	5	9	7
Higher National Diploma	5	5	4	–
Professional Certificates[Trade]	10	5	4	–
Bachelor of Science	10	9	4	6
Total	25	24	21	13

Legend: Product Production Officer-PPO; Quality Control Manager-QCM, Product Production Manager-PPM; ICTM- Information Communication Technology Manager

Table 5. Critical success enhancers of quality control monitoring in smart manufacturing.

Success Enhancers of Quality Monitoring Parameters	RAI	Rank
Strategic Flow system monitoring and evaluation	0.873	1st
Automatic rectification and fault diagnostic system	0.873	1st
Automatic design and calibration of quality control system	0.769	2nd
Up-to-date data generation transfer and harvesting	0.754	3rd
Smart and effective cost of quality control process	0.754	4th
System feed-back and monitoring strategy	0.732	5th
Effective training of manpower and human resources	0.653	6th
Ensuring man-machine system compatibility	0.623	7th
Setting up of smart system maintenance for extending machine live	0.610	8th

RAI–- Relative Agreement Index

Table 4. Profiling the state of adaptability of quality system monitoring in smart manufacturing.

Adaptability of Quality System Monitoring	Agreement Index	Rank
Platform design and calibration Platform	0.869	1st
Calibration platform with Sensor applications	0.786	2nd
Platform design and monitoring technology	0.771	3rd
Product process analytical system technology	0.754	4th
Operations research and technology	0.732	5th
Smart and Intelligent System for Sequencing	0.679	6th
Psychometric intelligent –based system	0.657	7th
Smart and Intelligent spindle system for quality assurance and monitoring	0.631	8th
3 D,4D and 5 D Design and Calibration System for quality monitoring	0.579	9th

Lekan et al. (2021)

thorough understanding of the censored variables (Niu, Kambe et al. 2018; Elhoone et al. 2017; and Illés et al. 2017).

Analysis of variance on factors influencing effectiveness of quality control monitoring

Parameters impacting intelligent manufacturing adaptation

With reference to Table 9, parameters that influences intelligent manufacturing adaptation was presented. Some of the parameters include: technology-based induced parameters, politically motivated parameters, economically oriented parameters and cyber security and digitalization. The presentation above toes the line of submission in order with presentations in the works of Levin (2010), Lichtblau et al. (2015); Xinyuan et al. (2017) and Li, Sethi. Similarly, Zhang describes economic factor as the main influencer of the adaptive change in intelligent manufacturing and production process. Levin (2010), Lichtblau et al. (2015), Xinyuan et al. (2017), and Kusiak (2018) has unified opinion about the influencing parameters in intelligent manufacturing adaptation, the study alludes that economic factors, technology-based factors and security system among others. This is similar to the submission in Manu (2014); Meng, Zhao (2018) and Mittal et al. (2019). Similarly, some of the factors describes stage transition from old method of application to conventional methods. For instance, Meng, Zhao (2018) and Mittal et al. (2019) suggested factors such as development related parameters, financial parameters, supply-chain management factors as an inducer of effective manufacturing. This factors was further reinforced in studies like Mirsanei et al. (2011); Miroslav, Martina, Radovan (2016) [49], Mukherjee et al. (2013) and Munir et al. (2013). Finally, Kagermann et al. (2013) alluded the fact that technology-based induced parameters, politically motivated parameters, economically oriented parameters and cyber security and digitalization are major game changer in influencing the effectiveness of intelligent manufacturing, this assertion was further reinforced in Nani, Yey, Lin (2015), Qu et al. (2019), Shady (2020), Wang and Freihert (2020), and Schmidt et al. 2015).

Mann-Whitney-U statistical t-test on critical factors influencing intelligent manufacturing adaptation

Statistical test was carried out on the data collated using Mann Whitney-U Test kits at 0.05 significant level of two tailed and the summary presented in Table 10. The values indicated high level of positive correlation among the respondents variables (Delloite 2016; ENQA 2019; Schumacher et al. 2016; Li et al. 2013; Wookkang et al. 2018; Holubek and Kostal 2012; Prístavka Miroslav et al. 2016; Liang et al. 2017).

Potential Disruption Tools for Product Enhancement in Intelligent Manufacturing was profiled and presented in Table 11. Conventional tools are necessary for fulfilling the functional integration of Artificial intelligence into the manufacturing sector. The tools are fitted with sensors that came along with the advent 20 of industry 4.0. Machines are also conventionally manufactured with knowledge of A.I. In Allon and Mieghem

Table 6. Mann–**Whitney**–***U*** **Student T**- analysis **on** agreement level on factors influencing effectiveness of quality control monitoring.

Statistic items	N	Mean	N	Mean	N	Mean	N	Mean	-	-
Man-**Machine**	0	1.500	1	1.500	1	1.500	1	1.500		
interaction	1	1.500	2	1.500	2	1.500	2	1.500		
Man/machin e configuration	2	1.500	1	1.500	1	1.500	1	1.500	–	–
	1	1.500	2	1.500	2	1.500	2	1.500	–	–
Quality control in data	2	1.500	1	1.500	1	1.500	1	1.500	–	–
	1	1.500	2	1.500	2	1.500	2	1.500	–	–
Cyber Security	2	1.500	1	1.500	1	1.500	1	1.500	–	–
	2	1.500	2	1.500	2	1.500	2	1.500	–	–
Intelligent maintenance	1	2.000	1	2.000	1	2.000	1	2.000	–	–
	2	1.5000	1	1.500	1	1.000	2	1.000	–	–
Data Acquisition	1	2.000	1	2.000	1	2.000	1	2.000	–	–
	2	1.000	2	1.000	2	1.000	2	1.000	–	–
Training Challenges	1	2.000	1	2.000	1	2.000	1	2.000	–	–
	2	1.000	2	1.000	2	1.000	2	1.000	–	–
Testing and Complexity	1	1.500	1	1.500	1	1.500	1	1.500	–	–
	2	1.5000	2	1.5000	2	1.5000	2	1.5000	–	–

Table 8. ANOVA of satisfaction level of facility managers on intelligent building systems' performance.

ANOVA

Performance Parameters		Sum of Squares	*df*	Mean Square	*F*	Sig.
Machine to machine	Between Groups	1.00	3	0.333		
	Within Groups	0.000	0			
	Total	1.000	3			
Man to machine	Between Groups	1.00	3	0.333		
	Within Groups	0.000	0			
	Total	1.000	3			
Data Quality	Between Groups	1.00	3	0.333		
	Within Groups	0.000	0			
	Total	1.000	3			
Cyber Security	Between Groups	2.750	3	0.917		
	Within Groups	0.000	0			
	Total	2.75	3			
Spare parts	Between Groups	2.000	3	0.667		
	Within Groups	0.000	0			
	Total	2.000	3			
Data Acquisition	Between Groups	2.750	3	0.917		
	Within Groups	0.000	0			
	Total	2.750	3			
Training Challenges	Between Groups	.750	3	0.250		
	Within Groups	0.000	0			
	Total	0.750	3			
Testing Cost complexity	Between Groups	1.000	3	0.917		
	Within Groups	0.000	0			
	Total	1.000	3			

Table 7. Chi-square analysis on factors influencing effectiveness of quality control monitoring.

	Production 0fficer		Quality Control Manager/Officer		Product Production Managers		ICTM Manager	
Factors/Parameters	PSI	KDTI	PSI	KDTI	PSI	KDTI	PSI	KDTI
Machine-Machine interaction	0.262	0.000	0.261	0.000	0.261	0.000	0.261	0.000
Compatibility of Man and machine	0.261	0.000	0.261	0.000	0.261	0.000	0.261	0.000
Presenting Quality Data	0.261	0.000	0.261	0.000	0.261	0.000	0.261	0.000
Availability Cyber Space Security System	0.238	0.030	0.238	0.030	0.238	0.000	0.238	0.000
Provision of Machine Spare Parts	0.238	0.164	0.238	0.164	0.238	0.091	0.238	0.091
Effective Quality Data Management	0.261	0.000	0.261	0.000	0.261	0.000	0.261	0.000
Capacity building and Training	0.261	0.391	0.261	0.391	0.261	0.261	0.261	0.204
Continuous Psychometric Data Testing	0.261	0.000	0.261	0.000	0.261	0.261	0.261	0.000

Ho: There is no divergent of opinion on factors influencing effectiveness of quality control monitoring.

Table 9. Critical parameters influencing intelligent manufacturing adaptation.

Parameters	PPM	Rk	QCM	Rk	PPM	Rk	ICTM	Rk
Technology-based induced parameters								
Technological Talents Cost	0.885	1st	0.863	1st	0.785	1st	0.783	2nd
Technological Failure Cost	0.883	2nd	0.861	2nd	0.721	5th	0.853	1st
Technological Skill Transfer	0.771	4th	0.757	5th	0.720	6th	0.759	4th
Cost of Check and Control	0.776	3rd	0.751	6th	0.698	7th	0.654	6th
Politically Motivated Parameters								
Government political intervention	0.766	7th	0.766	4th	0.658	9th	0.768	3rd
Control of Technological regulation and law	0.653	8th	0.655	7th	0.588	10th	0.657	7th
Provision of infrastructure environment	0.647	13th	0.645	8th	0.569	11th	0.456	14th
Intervention with Political power/influence	0.653	8th	0.765	3rd	0.767	3rd	0.745	5th
Economically Oriented Parameters								
Influence of Macro-economic parameters	0.557	11th	0.587	9th	0.435	13th	0.458	14th
Impact of micro-economic Parameters	0.766	7th	0.535	10th	0.677	8th	0.534	12th
Skill and technology knowledge sharing	0.765	5th	0.453	13th	0.786	2nd	0.523	13th
Cyber Security and Digitalization								
Influence of data security and storage	0.567	10th	0.536	12th	0.533	12th	0.653	8th
Homogeneity of law and regulation	0.553	11th	0.534	10th	0.767	3rd	0.653	9th
International permit and provision	0.463	12th	0.507	11th	0.767	4th	0.505	11th

Legend: Product Production Officer-PPO; Quality Control Manager-QCM,
Product Production Manager-PPM; ICTM- Information Communication Technology.

Table 10. Statistical analysis using Mann Whitney-*U* Statistical *t*-test on critical factors influencing intelligent manufacturing adaptation.

Parameters	Product Production	Production	ICT Officer	Control		Supervisor		Officer		
Technological Related Factor	1	1.300	1	1.300	1	1.300	1	1.300	–	–
Talent Investment Cost										
	2	1.300	2	1.300	2	1.300	2	1.300	–	–
Cost of variable failure	1	1.300	1	1.300	1	1.300	1	1.300	–	–
Exchange of Skill and Technological										
	2	1.300	2	1.300	2	1.300	2	1.300	–	–
Testing and Psychometric cost	1	1.300	1	1.300	1	1.300	1	1.300	–	–
Political Motivated Parameters										
	2	1.300	2	1.300	2	1.300	2	1.300	–	–
Government intervention/policy	1	1.300	1	1.300	1	1.300	1	1.300	–	–
Regulation of Technological context										
	2	1.300	2	1.300	2	1.300	2	1.300	–	–
Infrastructural procurement	1	2.000	1	2.000	1	2.000	1	2.000		
environment	2	1.000	2	1.000	2	1.000	2	1.000		
Availbility of Political Exchange will										
Economic-Motivated Variables Influence of micro-economic factors	1	2.000	1	2.000	1	2.000	1	2.000		
	2	1.000	2	1.000	2	1.000	2	1.000		
Influence of macro-economic factors	1	2.000	1	2.000	1	2.000	1	2.000		
Inter-continental technology transfer	2	1.000	2	1.000	2	1.000	2	1.000		
Interplay of Digital revolution	1	1.300	1	1.300	1	1.300	1	1.300	–	–
Data processing and management										
	2	1.300	2	1.000	2	1.000	2	1.300	–	–
High regulation requirement	1	1.300	1	1.300	1	1.300	1	1.300	–	–
	2	1.300	2	1.000	2	1.000	2	1.300	–	–
Large state space	1	2.000	1	1.300	1	2.000	1	2.000	–	–
	2	1.000	2	1.000	2	1.000	2	1.000	–	–

(2010), Tian et al. (2013), Webin (2019), Lekan et al. (2021), and Arijit, Abhijit, Sujit (2016), the applicability of disruptive tools was stressed; the study opined that engaging A.I. tools such as robots would prove more disruptive than any other type of inventions. Similarly, Abdul Rasid et al. (2014), Ahmad (2017), Skrop et al. (2018) and Steven, Manik, Xianli, Caixu, Pan and Lihui (2017) described some of the tools that provide cutting edge services in production management to include cloud storage, sensors, virtual reality tools, and computer vision. The view expressed by the authors backs up the claim, as presented in Table 11 as touching product enhancement tools in intelligent based machine is ranked 1st by three groups of the respondents P.S., PM, and Q.C.O. with mean scores 4.876 and 4.360 respectively. The artificial intelligence package was ranked 2nd by P.S., PM, and Q.C.O. with mean scores 4.360, 3.920, and 4.315, respectively, while the artificial intelligence package is ranked 1st by ICTO. Machine vision tools are ranked 3rd by P.S., Q.C.O., and ICTO with mean scores 3.605, 4.305and 3.825, respectively. Some tools are ranked least; this includes natural language converter, computer vision, and image mapping tools, that are ranked 11th and 12th. Image mapping and recognition tools are ranked least (13th) of all the tools by PM, Q.C.O., and ICTO with mean scores 3.390, 2.670, and 2.265, while automatic speech recognition was ranked 12th by P.S., Q.C.O., and ICTO, respectively, this is supported in Sinha (2020), Singh et al. (2012), Su and Liu (2015), Cloud (2014), Mrugalska and Tytyk (2015), and Panda (2018).

Potential disruption tools for product enhancement in intelligent manufacturing

Deployment of disruptive innovation in intelligent manufacturing system

Strategy for deployment of Disruptive Innovation in Intelligent Manufacturing System is presented in Table 12. Innovation is key to every sustainable development, and there are specific ways

Table 11. Tools for product enhancement in intelligent manufacturing.

Disruptive Tools	PS		PM		QCO		ICTO	
Cloud based machine	Mean 4.876	Rank 1st	Mean 4.360	Rank 1st	Mean 4.360	Rank 1st	Mean 3.830	Rank 2nd
Artificial intelligence package	4.360	2nd	3.920	2nd	4.315	2nd	3.840	1st
Machine vision tools	3.855	7th	3.605	3rd	4.305	3rd	3.825	3rd
Smart maintenance	3.880	3rd	3.600	4th	3.835	4th	3.760	4th
Engaging virtual reality tools	3.870	6th	3.490	5th	3.750	5th	3.750	5th
Robotics automation	3.880	3rd	3.276	7th	3.750	5th	2.660	6th
Internet of things	3.265	10th	3.285	6th	3.810	7th	3.775	7th
Product design through Intelligence Artificial	3.235	12th	3.285	8th	3.255	8th	3.765	8th
Machine Translation	3.265	10th	2.840	9th	3.215	9th	2.655	10th
Computer vision	2.765	11th	4.125	10th	3.210	10th	2.678	9th
Natural Language converter	2.785	9th	2.815	11th	2.880	11th	2.515	11th
Automatic speech recognition	3.880	3rd	2.155	12th	2.835	12th	2.490	12th
Image mapping and recognition tool	3.825	8th	3.390	13th	2.670	13th	2.265	13th

Table 12. Strategy for deployment of disruptive innovation in intelligent manufacturing system.

Disruptive Tools	PS Mean	Rank	PM Mean	Rank	QCO Mean	Rank	ICTO Mean	Rank
Intelligent need validation	4.355	3rd	4.435	2nd	4.230	2nd	4.380	1st
Intelligent product plan design	4.365	1st	4.455	1st	4.270	1st	4.325	2nd
Intelligent production operation process	4.360	2nd	4.375	3rd	3.855	3rd	4.310	3rd
Intelligent production operation process	3.945	4th	4.335	9th	3.780	4th	4.285	4th
Intelligent quality control	3.895	5th	4.375	3rd	3.715	5th	4.275	5th
Intelligent product packaging	3.880	6th	4.325	8th	3.670	6th	3.770	6th
Intelligent maintenance of quality process	3.835	7th	4.330	7th	3.655	7th	3.760	7th
Intelligent product deployment	3.490	10th	4.365	5th	3.445	8th	3.755	8th
Pilot study	3.495	9th	4.355	6th	3.390	9th	3.265	9th

an innovation should take in deployment and implementation. Some of the disruptive tools censored in this context include the following: Intelligent need validation; intelligent product plan design; intelligent production operation process; intelligent production monitoring process; intelligent quality control, intelligent product packaging, intelligent maintenance of quality process, intelligent product deployment, pilot study, product calibration, product innovation development, product innovation diffusion, and technological administration management. Intelligent product plan design was ranked 1st by P.S., PM, and Q.C.O. with mean values of 4.365, 4.455, and 4.270, respectively. Intelligent need validation was ranked 2nd by PM, Q.C.O., and ICTO, with mean scores 4.435, 4.230, and 4.380, respectively. Likewise, intelligent production operation processes and intelligent production monitoring processes were ranked 3rd and 4th, respectively. Intelligent quality control was also ranked 5th by P.S., Q.C.O., and ICTO. The tools are mainly composed of an advanced state of artificial intelligence (A.I.), for instance Lanza et al. (2016), Levin (2010), and Lichtblau, Stich, Bertenrath, Blum, Bleider, Millack, Schmitt, Schmitz, Schroter, (2015) opined that the majority of intelligent tools are A.I. compliant and the aim is to create a seamless production system. In Lichtblau, Stich, Bertenrath, Blum, Bleider, Millack, Schmitt, Schmitz, Schroter, (2015), some quality control tools used in intelligent manufacturing are mentioned, such as sensor heads and control charts. Similarly, the cost of quality is high, and the main aim of the disruption is to eliminate some costs usually incurred during the production process. Therefore, Lichtblau, Stich, Bertenrath, Blum, Bleider, Millack, Schmitt, Schmitz, Schroter, (2015) profiled some factors that influence costs to include, among other things, product type, the extent of publicity on quality awareness, extra incurable cost, among others. The opinion in Lichtblau, Stich, Bertenrath, Blum, Bleider, Millack, Schmitt, Schmitz, Schroter, (2015), therefore, toes the line of submissions in Feigenbaum (1991), and Nani et al. (2015).

Conclusion

The study has dwell extensively and tried to validate the content of the aim and objectives of the study and concepts highlighted in the title. The study has duly presented the issues, facts, ideals and factors that influences the adoption of disruptions in creating adaptive intelligent manufacturing with a view to creating enhanced productivity in intelligent manufacturing. Literature review fixed background for identification of gaps so as to enable contribution to knowledge and literary presentations. The outcome of the survey indicated that majority of the respondents submitted that the concept of intelligent manufacturing is gradually gaining ground as compared with experience of advanced countries like Germany, United Kingdom, United States and the like. This was supported by Bierma and Waterstraat (2001), Brüggemann and Bremer (2012), Fansheng and Gang (2018), Bourne and Fox (1984), Teixidor et al. (2013), and Teixidor et al. (2013). Similarly, there are number of adaptable disruptions of intelligent manufacturing being identified in the study, this include: Artificial intelligence package, Machine vision tools, Smart maintenance, Engaging virtual reality tools, Robotics automation, Internet of things, Product design through Intelligence, Artificial, Machine Translation, Computer vision, Natural Language converter, Automatic speech recognition and Image mapping and recognition tool. Furthermore, critical success enhancer of managing quality control system in intelligent manufacturing was also one of the highlight of the study, some of the success enhancers includes; strategic flow system monitoring and evaluation, automatic rectification and fault diagnostic system, automatic design and calibration of quality control system, up-to-date data generation transfer and harvesting, smart and effective cost of quality control process, system feed-back and monitoring strategy, effective training of manpower and human resources, ensuring man-machine system compatibility and setting up of smart system maintenance for extending machine live. This was further supported by Wen Gan (2017 and Niu, Qin et al. (2018) and Zaidin et al. (2018). There are potential challenges involved in the effective monitoring of quality in intelligent manufacturing and production process, machine design, product design, cyber- attack, technological transfer restriction, unavailability of resources, data security challenge and training/ recruitment challenges. This study presents emerging areas of application of quality monitoring system in intelligent manufacturing to include advanced analytical tools and censored based applications such as robotics applications used in design and product calibration, virtual and augmented reality application that simulates real situation using virtual approach, machine learning, expert systems (AI), block chain technology, drones for real time supervision of production process to improve quality in manufacturing process. The interdependence of smart manufacturing and intelligent production were presented and cross validated in this study (Webin 2019; Su and Liu 2015).

Study limitation

This study was limited to the study of areas of disruptions in intelligent manufacturing, focusing on the managing of quality control system. The study was also restricted to qualification approach to the findings of the research subject. The area of research is restricted to African with Nigeria as a context to create production scenario to follow after the development in the advanced world like USA, UK, Germany, France, Italy, Belgium and many other advanced countries.

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