COVID-19 DISRUPTIONS: DATA DRIVEN RESTRUCTURING OF GLOBAL MANUFACTURING FOR ENHANCED COMPETITIVE ADVANTAGE

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Abstract: *This paper reviews the weaknesses of global manufacturing as per problems of quality, equipment maintenance, local inputs, innovation and responsive agility; which have become much worse, no thanks to the Covid-19 pandemic. It discusses the nature, capability and novel applications of Artificial Intelligence (AI) and Big Data Analytics (BDA) towards Covid-19 compliant new normals in supply chains and manufacturing systems redesign. Anchored on the need for enhanced transparency, accessibility, real time data interchange, contactless transactions, self-service and several other unprecedented business practices, the study presents a comprehensive review of the global influence of AI and BDA, and justifies their potential applications in Nigeria. The goal is for manufacturing operations to become more proactive, agile; less vulnerable to disruptive shocks; and capable of an optimal arrangement of people, machines, systems and processes across all supply chain touch-points. The paper also stresses the limitations of real time contactless digital tools in a developing nation and calls for more discussions, research and advocacy. The study is theoretical. It critically analyses the foregoing perspectives and proposes a framework for a Covid-19 compliant sustainable manufacturing supply chain. The study is significant because it focuses attention on the impacts of Covid-19 pandemic on Nigerian manufacturing, the potentials of AI/BDA in mitigating supply chain disruptions and what data-based applications are justifiable or appropriate in Nigeria as the pandemic new normals.*

Keywords: *Supply Chain Redesign; Covid-19 Pandemic; Artificial Intelligence; Big Data Analytics; Nigerian Manufacturing.*

1. INTRODUCTION

The world has experienced several immense disruptions and recoveries from natural and man-made disasters-earthquakes, tsunamis, active/passive wars and workers' strikes. However, In February and early March 2020, the number of COVID-19 cases had exponentially increased in Asia, Europe and USA resulting in border closures and quarantines. Meanwhile, several developing countries panicked as resources, knowledge and citizens compliance with the statutory regimes were not adequate (Okeya-Olayinka & Ogundele, 2022).

The COVID-19 pandemic has compelled a greater range and depth of operations support technologies globally (Wang, Tiwari, & Chen, 2017; Dubey, Gunasekaran, Childe& Wemba, 2019; Ivanov & Dolgui, 2020). In the circumstance, tools/systems are being developed and deployed to identity, isolate, master, recover and fortify systems against disruptions real-time. AI and BDA are central to the efforts to anticipate, shield and recover speedily to maximize throughput, inventory flows, appropriate buffer stocks, real-time information access, the realities of production plans, and responsive agility(Subramanian & Abdulrahman, 2017; Ivanov & Dolgui, 2020).For example, through the use of radio frequency identification chips (RFID), Internet of Things (IoT) devices and extended Enterprise-wide Resource Planning (EERP) solutions, production systems have been able to ascertain risk exposures and do business in a manner that parts, samples, products, deliveries and sales are seamlessly processed in an open digital environment. The challenge facing manufacturing is how to re-engineer and adopt Cocid-19 imposed technological enablement, mainly through BDA and AI applications to add value.

As supply chains expand and integrate globally to effectively achieve greater volume flexibility, market concentration, cost/quality decoupling, and compressed time to market, the Henry Ford type of mass production factories could suffer great disadvantage, to be further compounded by disruptive Covid-19 pandemic effects. Businesses that aim to trade and seek competitive advantage globally but fail to adopt and apply AI/BDA technologies appear set for extinction both in terms of investment and patronage (Scheibe & Blackhurst, 2017;Ivanov & Dolgui, 2020). This perhaps accounts for news media reports in Nigeria that investment flows to the manufacturing sector has fallen by over 75% in the last one year.

Specifically, this study seeks to answer the following questions:

- What are the impacts of COVD-19 pandemic on global manufacturing and SC practices?
- To what extent do AI and BDA mitigate the COVID-19 pandemic induced disruptions?
- What could be the appropriate applications for the less developed Nigerian manufacturing?

The rest of the paper is organised a follows. Section 2 reviews the literature on the Covid-19 pandemic disruptions and the data-driven recovering models in global manufacturing. Section 3 discusses the methodology of the study, Section 4 analyses the results while Section 5presents the conclusions.

2. LITERATURE REVIEW

This section reviews the related literature on the subject of the study.

2.1 Meaning and Purpose of AI/BDA

Big Data Analytics (BDA)is a complex process of storage, retrieval, interchange and processing of massive unstructured and semi-structured data in multiple platforms, using suitable algorithms to sort, unsort, relate, differentiate and extract useful information for precise and real time decision making (Einav & Levin, 2013). Covid-19 enhanced applications of AI epitomise the increasing capability of programmed machines to perform roles and tasks currently performed by humans. The idea of AI is to use the principle of applying the knowledge of how the human brain functions to develop sophisticated software-driven machine intelligence that could learn and respond to business problem situations, analyse unstructured data intelligently over and above what is possible in the real world. Through AI, thinking machines capable of mimicking, learning, unlearning and replacing human intelligence have been developed (Hokey, 2010). Recently, the US media reported the development and deployment of AI empowered floating robots used to clean harbours and the oceans.

Bernard Marr, author of Big Data, pointed out that through simulations, the digital twin model leverages the Internet of Things (IoT), prevents downtime, develops new opportunities, plans for the future, but requires the skills of machine learning and artificial intelligence. In the same vein, Ivanov and Dolgui (2020) maintained that digital twin pairs the virtual and physical worlds by allowing the analysis of data and monitoring of systems to head off problems before they occur. The authors also confirm that this technique represents physical supply chain based on actual transportation, inventory, demand, and capacity data, and can therefore be used for planning and real-time control decisions. According to Daugherty & Wilson (2018), AI enabled systems are expanding rapidly, transforming manufacturing and other operations, and traversing into what had normally been exclusive human domains.

Accordingly, corporate giants like Google, IBM, Facebook, Yahoo, Intel, Apple are competing to acquire private AI companies, with Ford, Samsung, GE and Uber emerging as new entrants, all in a bid to accelerate their AI systems innovation (Jean-Paul, 2019). There is also the evidence that e-commerce firms that use BDA in their operations are experiencing some five to six percent higher productivity relative to other competitors (Salleh and Janczewski, 2016). The economic impact of AI was also assessed by the World Economic Forum, who project that twenty percent of current jobs could be impacted and that 133 million new jobs would be created world-wide by 2022. It has also been highlighted that global spending on AI technologies within the consumer retail sector alone could be up to twelve billion dollars by 2023, rising from the current figure of three and a half billion dollars. These figures are greater in emerging economies such as China and India, where the level rises to twenty-six percent (26%) due to the greater scope for technological change within the manufacturing sector. Furthermore, research conducted by IDC (Yogesh et al., 2019) indicated that AI spending in Europe for 2019 increased by forty-nine percent over 2018 to a figure of over five billion dollars; and that AI technology is predicted to contribute twenty percent of the Chinese GDP by 2030.

2.2. Magnitude of the Disruptions

As many governments imposed lockdowns to stop and control community transmission of Covid-19, there was a shortage of labour and supply-side shocks across industrial sectors and nations (et al, 2020).The disruptions diminished Chinese exports to global supply chains even as the operations of 94 percent of the Fortune 1000 companies were devastated. A corporate data analytics firm, Dun and Bradstreet reported that 51,000 companies around the world have one or more direct suppliers in Wuhan and at least 5 million companies around the world have one or more tier-two suppliers in the Wuhan region, the origin and epicentre of Covid-19 (Ivanov & Dolgui, 2020).

Hence, according to Resilinc System Incorporated, the world’s largest 1,000 firms who own more than 12,000 facilities including factories and warehouses in the Wuhan long-term quarantine areas, suffered adverse disturbances and losses (Linton & Vakil, 2020). Tang (2006) reports that 43 percent of 142 supply chain companies across consumer goods and health care became vulnerable, even as 55 percent of them had no formal contingency plans. This means so much unmanaged supply chain risk. The foregoing illustration underscores the need to mitigate supply chain risk through the application of AI/BDA to control and aid post covid-19 recovery. The goal would be to protect supply chain dependability, agility and resilience (Altay et al., 2018; Olivares-Aguila & Elmaraghy, 2020).

2.3 AI/BDA Deployment to Mitigate the Disruptions

Recent studies have identified different classes of digital technologies including BDA, advanced manufacturing technologies (AMT) with sensors, decentralised agent-driven controls, advanced robotics, augmented reality, advanced tracking/tracing technologies and additive manufacturing, as well as their relative impacts on supply chain responsiveness and sustainability (Ben-Daya et al., 2018; Nguyen et al., 2017; Hofmann 2017; Choi et al., 2018; Gunasekaran et al., 2017). Khajavi et al. (2014) and Ivanov (2020) illustrated how additive manufacturing could lead to the possibility of producing modules, components, and end products in one location, and dynamically at any other SC points if some factories, suppliers, decision centres and transportation links become temporarily unavailable. This is to prevent material shortages and delivery delay propagation in the downstream supply chain, and the attendant diminution of revenues, service levels and productivity (Garvey et al., 2015, Dolgui e t al., 2020, Ivanov et al., 2019, Pavlov et al., 2019, Dolgui et al., 2020, Goldbeck et al., 2020, Li and Zobel, 2020).

These adaptations as well as mechanization and process automation generating volumes of data that is more than most companies know what to do with; provide incontrovertible support for more AI/BDA-led digital techniques.When fed into analytical software, such data could yield valuable information to improve manufacturing process efficiency- cost savings, better quality and enhanced collaboration. For instance, a factory sensor could generate thousands of data points when scanning for defects along the assembly line, even as data mapping could assist the visibility of supply chain networks (Ivanov and Dolgui, 2020; cited by Ogbuke et al., 2020).

The beauty of AI is its ability to independently interpret and learn from external data and achieve specific outcomes via flexible adaptations (Kaplan & Haenlein, 2019). It can ingest a combination of data from sensors, machines and people, and then apply algorithms designed to optimize operations or achieve robotic lights out capabilities. Covid-19 induced DBA/AI applications are also in vogue in education, healthcare, finance, marketing, transport, security and entertainment. For example, AI systems are already helping oncologists to identify cancerous tumours, whilst education robots are teaching coding to school children. AI has been applied to predictive policing and traffic control (Hokey, 2010; Klumpp, 2018), using the virtual mirror and visual search to improve customer interaction and narrow the gap between the physical and virtual shopping (Yogesh et al., 2019).Applications in the healthcare and retail sectors include the use of hand-held scanners for contactless shopping, medical consulting and sample/specimen collection. Amazon already uses AI in many aspects of its business, including ordering robots in warehouses, identifying scenes in movies, and voice-recognition services.

As more businesses aim to improve trend analysis, logistics planning and inventory control, AI is to play critical roles in the envisioned Smart Factory/Industry 4.0; which aim to realize a highly inter-connected, optimised and autonomous system with little human input (Klumpp, 2018).

Zhong et al. (2015) proposed a big data approach for forecasting logistics using RFID enablement even as some other researchers (Sommerfeld et. al., 2018; Nguyen et al., 2018; cited by Ivanov and Dolgui, 2020) reported the effects of sensor-based simulation of quality data in an automotive supply chain. It has also been confirmed that data analytics improves supply chain resistance to risk exposures and resilience (Choi & Lambert, 2017; Papadopoulos et al., 2017).

Resilience360 at DHL enables compressive disruption of risk management by mapping the SC end-to-end building risk profiles, and identifying critical hotspots in order to initiate mitigation activities and deliver alerts, in near-real time, about incidents that could disturb SC. According to Ivanov and Dolgui, (2020), decisions in SCs risk management are frequently brought into correspondence with disruption profiles, which contain the stages of pre-disruption (preparedness), disruption (response), and post-disruption (recovery and stabilisation). The authors maintained that Optimisation and simulation models enable robust SC design, resilience analysis, and stress-testing-testing of different alternative SC design, and simulation of contingent recovery policies.

The application of these digital technologies becomes more crucial in emerging trends such as prediction of geospatial disease, understanding consumer behaviour during natural disasters such as hurricanes and pandemic outbreaks, analysing the roles and public behaviours through social network data mining, blockchain-based transportation control, managing traffic flow during catastrophic events, as well as maximum optimisation coverage and safety locations of relief facilities (Apte et al., 2016; Araz et al., 2013; Yucel et al.,2018; Choi, Wallace, and Wang, 2018; cited by Inavov and Dolgui, 2020). Furthermore, In the vision of the industry 4.0, some scholars predicted that the digitisation of firm processes will facilitate the integration of firm functions and supply chain members, in a manner that 'chain' becomes a completely integrated ecosystem that is fully transparent to all the players involved, namely: from the supplier of raw materials, components, and parts, to the transporters of those supplies and finished goods, and finally to customers demanding fulfilment (De Sousa Jabbour et al., 2018).

Some scholars have acknowledged the difficulty in predicting and detecting the disruptions that vary in type and nature, and are too intermittent and irregular to be identified, estimated or forecasted well (Pettit, Fiksel, and Croxton, 2010; Bhattacharya et al., 2013; Ambulkar, Blackhurst and Grawe, 2015; cited by Inavov and Dolgui, 2020). In addition, establishing a robust supply chain management strategy through the application of analytics technologies has become very challenging, particularly in the ongoing Covid-19 pandemic. Accordingly, AI seems set to be the most important competitive enabler in the years ahead.

2.5 Sustainable supply chain, restructuring models and post Covid-19 recoveries

According to European Commission (EEA, 2019), post-COVID-19 recoveries will afford rare circumstances to shift supply chain and production systems toward a more desirable state, particularly for changes in public policy and financial investment. Although these institutions maintained that macroeconomic systems, sustainable global supply chains, and international trade relations should not be allowed to change to the 'new normal.' This crisis has also created opportunities for people to build new skills and shift away from energy-intensive forms of transportation to adoption of telecommunication, virtual meetings, and online education.

It is expected that post COVID-19 recoveries will prompt business managers and policy makers to re-examine prevailing globalised systems of production based on complex value chains and international shipment of billions of components and likely prompt establishment of new relationships and supply configurations (Sarkis et al., 2020). Most vulnerable to the corona virus pandemic were the just-in-time (JIT) and lean delivery systems. Required is the application of smarter logistics systems, including reverse logistics for secondary materials and waste products and enabled by Internet of Things (IoT) technologies. The goal would be localisation of the global network and online sharing platforms (Terry et al., 2014) for enhanced traceability and transparency in supply chains (Shim et al., 2019).

This review identified the successful elements of risk mitigation/preparedness and recovery policies for epidemic outbreaks. The need arises to address the following research questions:

i. What are the impacts of COVD-19 pandemic on sustainable global SC practices?
ii. To what extent do AI and Big Data Analytics influence/mitigate SC disruptions and the potential applications of technologies in the effort to manage COVID-19 pandemic?
iii. What will be the applications for the restructuring processes of a new global manufacturing supply chain model?

2.6 Negative Impacts/Limitations of the AI/BDA Applications

There are two routes an organization should consider in answering these questions. The first is to assess the readiness of a manufacturing organization's ability to design and implement AI-based solutions in-house. The second is the ability to leverage AI-based solutions and expertise as part of commercial offerings.

Most organizations lack the skill-sets, scientists, data, and infrastructure readiness to pursue unique differentiating processes or solutions. Today, most manufacturing organizations have disconnected machines, people, and processes, all of which are not particularly suited to AI or machine learning (ML). One is more likely to find paper than a technical foundation for implementing and accelerating artificial intelligence. In this respect, the manufacturing trade has a long way to go—but don't let that dissuade your organization from experimenting and investing in artificial intelligence. Like with other longer-term initiatives, it takes time to up-skill employees, change the culture, and implement some of the underlying investments necessary to tackle artificial Intelligence.

A survey conducted by Byed TA (1993) involving a large number of knowledge engineers that adopted the use of Expert System (ES) in productions and operations showed limited results. The findings concluded that whilst this is very promising application area, many of the interested organisations using or developing large numbers of ES have published relatively little of the work due to the secrecy under which such commercially valuable systems tend to be developed (Efros et al., 2018; Russell et al., 2019).

We briefly discuss some negative impacts of AI as follows.

1. AI Bias

Since AI algorithms are built by humans, they can have built-in bias by those who either intentionally or inadvertently introduce them into the algorithm. If AI algorithms are built with a bias or the data in the training sets they are given to learn from is biased, they will produce results that are biased. This reality could lead to unintended consequences like the ones we have seen with discriminatory recruiting algorithms and Microsoft's Twitter chatbot that became racist. As companies build AI algorithms, they need to be developed and trained responsibly.

2. Loss of Jobs

While many jobs will be created by AI and many people predict a net increase in jobs or at least anticipate the same amount will be created to replace the ones that are lost thanks to AI technology, there will be jobs people do today that machines will take over. This will require changes to training and education programmes to prepare our future workforce as well as helping current workers transition to new positions that will utilise their unique human capabilities.

3. A shift in Human Experience

If AI takes over menial tasks and allows humans to significantly reduce the amount of time they need to spend at a job, the extra freedom might seem like a utopia at first glance. However, in order to feel their life has a purpose, humans will need to channel their newfound freedom into new activities that give them the same social and mental benefits that their job used to provide. This might be easier for some people and communities than others. There will likely be economic considerations as well when machines take over responsibilities that humans used to get paid to do. The benefits of increased efficiencies are pretty clear on the profit-loss statements of businesses, but the overall benefits to society and the human condition are a bit more opaque.

4. Global Regulations

While our world is a much smaller place than ever before because of technology, this also means that AI technology that requires new laws and regulations will need to be determined among various governments to allow safe and effective global interactions. Since we are no longer isolated from one another, the actions and decisions regarding artificial intelligence in one country could adversely affect others very easily. We are seeing this already playing out, where Europe has adopted a robust regulatory approach to ensure consent and transparency, while the US and particularly China allows its companies to apply AI much more liberally.

5. Accelerated Hacking

Artificial intelligence increases the speed of what can be accomplished and in many cases, it exceeds our ability as humans to follow along. With automation, nefarious acts such as phishing, delivery of viruses to software and taking advantage of AI systems because of the way they see the world, might be difficult for humans to uncover until there is a real quagmire to deal with.

6. AI Terrorism

Similarly, there may be new AI-enabled form of terrorism to deal with: From the expansion of autonomous drones and the introduction of robotic swarms to remote attacks or the delivery of disease through nanorobots. The law enforcement and defence organisations will need to adjust to the potential threat these present.

According to Yogesh et al. (2019), these challenges are driven by a combination of the the changing nature of the business environment, the nature of AI and machine learning (ML) themselves, and underlying data information theory limitations that apply to all information processing aligned to AI. In supply chain for example, there is the bottlenecks of assimilating vast quantities of data and turning them into useful information rapidly enough to respond to turbulent change (Vadera et al., 1998).

Again the volume of the data are far too great for manual analysis and there are also limited scope for the development of computer-based systems to provide automatic application of model and optimisation, as well as the required skill sets in terms of employees in handling this machine systems. Other barriers that AI adoption may experience, according to Manyinka et al. (2017) are unmanaged impacts on jobs, inequality, ethics, privacy and democratic expression. The authors pointed out that whilst the benefits of greater level of AI adoption within many sectors of the global economy are felt in the context of greater efficiency, improved productivity and reliability, this picture of positive innovation is not universally welcome globally, particularly in the aspect of workforce and less technologically endowed economies.

Moreover, society is yet to fully grasp with many of the ethical and economic considerations associated with AI and Big Data and its wider implications on human life, culture, sustainability, and technological transformation. To this end, firms are now at a crucial juncture in determining how to effectively deploy these anti-disruption technologies that will promote, rather than hinder societal/democratic values such as personal well-being, freedom, equality and transparency.

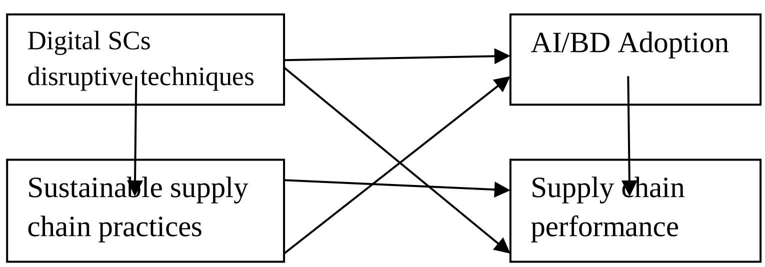
2.7 Conceptual model

In line with the fore-going review of literature, the study proposes a conceptual model of four major constructs to provide business and managerial insights on the requirements for recovering from COVID-19 induced SC risk and disruptions. The four constructs are namely: Digital SCs disruptive techniques, Supply chain performance, Sustainable supply chain practices and AI/BD Adoption. The literature review has already demonstrated significant relationships among these four constructs. As yet however, empirical evidence remains vague.

The recent COVID-19 pandemic affected the global supply chain performance of most organisations, particularly in manufacturing sector. In fact, the demand for most essential products such as toilet papers and hand sanitizers increased significantly; likewise the supply of the raw materials (Kumar 2010). According to Ivanov and Dolgui (2020), AI and big data analytics can be deployed in managing supply chain disruptions by enhancing firm's resiliency, cost effectiveness, and improve flexibility and adaptability. The authors further confirm that these disruptive technologies have the capacity to improve predictive and reactive decisions, utilize the advantages of SC visualisation, ensure end-to-end visibility, as well as business performance in global companies.

The digital SCs disruption techniques – This construct indicates that the major drivers of the digital tools are massive increase in supply chain data, computational power, ability to harness data into useful business insights and labour productivity. Several studies supported these perspectives. Choi, Chan, and Yu (2017) and Ivanov et al. (2020) contended that the substantive areas of data analytics and digital application is massively dependent on the volume, velocity and varieties of supply chain data, both structural and unstructured that may provide useful insights for SC risks managers and for dealing with SCM including warehousing, joint demand planning and inventory control (Hokey, 2010).

Figure 1. Conceptual Model of Impact of Digital Techniques on COVID-19 SC Disruptions



The variables for sustainable supply chain practices include: Intelligent automation, accelerating innovation, restructuring models and designs, real-time decision-making, disruptions and risks management, and collaboration. For example, Kumar and Chowdhury (2020) in their study designed a recovery and restructure model that is capable of revising the production plan in the situations of both demand and supply disruptions, and has the potential to significantly improve profit margins for manufacturers. For AI and Big Data adoption, significant uptake and adoption has been reported; which have led to improved productivity and reliability (McKinsey, 2020).

2.8 Management theory

The management theory that underpins this study is the dynamic capabilities views. This theory is an extension of the relational theory (Geyi et al., 2019). Primarily, the resource-based theory examine how key assets and capabilities serve as a base for competitive advantage and superior performance. In other word, AI, and Big Data Analytics provided the innovation and capabilities the SC firms and risk manager may use to maintain or improve their competitive position and performance objectives. However, according to Hart (1995; cited by Geyi et al., 2019), there are criticism about the relevance of resource-based view theory to current sustainable supply chain design. The author pointed that in propounding a natural resource-based view, models of sustainable competitive objective need to include the constraints and challenges, particularly within the natural environment of the firms, as well as how the internal resources and capabilities of the firm's natural environment can result to competitive advantage.

Hart and Dowell (2011; cited by Geyi et al., 2019) explored further the natural Resource-Based View of the firm in the light of dynamic capabilities. The roles were examined to understand how organisations account for supply chain sustainability in their desire to gain competitiveness. More so, Ketchen and Hult (2007) emphasise that firms should rather invest in organisation that allows them create collaborative relationship rather than firm-specific rent. Over all, these perspectives suggest that dynamic capabilities view is critical because it provide greater insight into understanding both what drives organisations for value creation and what leads to competition for value capture.

3. RESEARCH METHODOLOGY

A detail review of the literature was carried out on the technologies of industry 4.0, particularly artificial intelligence (AI) and Big Data Analytics, and their capabilities in handling supply chain disruptions occasioned by Covid-19 pandemic. The study employed appropriate search words on the database of PubMed, Scopus, Google Scholar and Research Gate. This paper first clarifies the phenomenon and then gives an overview of its present scope.

The study looks at various applications of AI and Big Data Analytics, highlighting some of the leading industrial sectors in the field. Although the research focused more on the application of AI, Big Data within the supply chain management, the research outline the leading industry sectors as provided in Figure 1. This paper described the nature and context of these concerns, reviews the current state of the economic impacts of these disruptive technologies, as well as their capacity and mitigating influence in addressing supply chain disruptions, majorly orchestrated by COVID-19 pandemic. The paper substantially enriched the body of literature and significantly contributed to this emerging debate by specifically addressing the research questions stated earlier in section 2.5.

However, some other works that reported the application areas of this review were limited and rather unsystematic. More so, the prior reviews dwelled little on the impacts of COVID-19 pandemic and potential outbreaks on SC disruption management and performance. There was no compressive framework to conceptualise and identify valuable insights that could enable SC risks managers make appropriate decisions in the event of future pandemic occurrences.

4. DISCUSSION

The applications of AI and Big Data digital tools have been adequately discussed in this paper. We found several usefulness of AI and Big data technologies which played significant roles for the proper control and management of Coviv-19 pandemic, particularly for the detection and diagnosis of Covid-19 and other related epidemic incidences and symptoms (see table 1). In combating supply chain disruptions, the studies gave several applications and industry leading sectors (see figure 1). The paper also acknowledged that many business leaders are uncertain about what exactly AI/Big Data can do, as the adoption is slow and remains in its infancy stage.

In fact, the study reveals that despite the excitement over the Industry 4.0 technologies, two-third of the opportunities to use AI and Big Data are in improving the performance of existing analytics users and they do not appear to have been adopted on a large scale (Jean-Paul, 2019). The study also recognised that there may be a discrepancy between breakthroughs in AI in the academic research community and commercial applications. More so, even in the promising field of Machine Learning (ML), demand is rather uncertain and not only on the business side, but also on the consumer side. The wiliness of consumer to adopt for example, the much celebrated AI-powered virtual assistances is also very uncertain. Overall, one of the major challenges of these digital tools include regulations of data and algorithms; the (mis-) measurement of value added; market failures, anti-competitive behaviour and abuse of market power, surveillance, censorship, cybercrime; labour market , discrimination, declining job quality; and AI in emerging economies (Naude-Wim, 2019).

5. CONCLUSION AND FURTHER RESEARCH

This paper shows that AI and Big Data Analytics research, investment and applications are booming, across most industries, business community, governments and academic institutions world-wide. The study specifically explored the importance and limitations of these digital capabilities in solving COVID-19 pandemic disruptions in Nigerian manufacturing. In this reviews, theoretical and empirical arguments suggest that AI and Big Data Analytics have the prospects of addressing the COVID-19 incidence and any other future supply chain disruptions (Ivanov, 2020) particularly in order processing, plant operations, production control and sales management; and that Nigerian organizations need not sit on the fence.

However, AI and Big Data have both hopes and fears. Economists for instances, have concerns about the impacts of AI on employment, job quality, inequality and competition. They are expensive to adopt especially by SMEs and are also hard to justify on computation requirement, environmental cost and job creation. Further research is required on the social, economic and political impacts of AI and Data Analytics, particularly on jobs and inequality.

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