Role of Institutional Pressures and Resources in the Adoption of Big Data Analytics powered Artificial Intelligence, Sustainable Manufacturing Practices and Circular Economy Capabilities

Surajit Bag
Post Graduate School of Engineering Management
University of Johannesburg, South Africa
Email: surajit.bag@gmail.com

Jan Harm Christiaan Pretorius
Post Graduate School of Engineering Management
University of Johannesburg, South Africa
Email: jhcpretorius@uj.ac.za

Shivam Gupta
Department of Information Systems, Supply Chain & Decision Making
NEOMA Business School, 59 Rue Pierre Taittinger, 51100 Reims, France
Email: shivam.gupta@neoma-bs.fr

Yogesh K. Dwivedi (Corresponding Author)
Emerging Markets Research Centre (EMaRC), School of Management, Swansea University, Bay Campus, Swansea SA1 8EN, UK
Email: y.k.dwivedi@swansea.ac.uk

ABSTRACT

The significance of big data analytics-powered artificial intelligence has grown in recent years. The literature indicates that big data analytics-powered artificial intelligence has the ability to enhance supply chain performance, but there is limited research concerning the reasons for which firms engaging in manufacturing activities adopt big data analytics-powered artificial intelligence. To address this gap, our study employs institutional theory and resource-based view theory to elucidate the way in which automotive firms configure tangible resources and workforce skills to drive technological enablement and improve sustainable manufacturing practices and furthermore develop circular economy capabilities. We tested the research hypothesis using primary data collected from 219 automotive and allied manufacturing companies operating in South Africa. The contribution of this work lies in the statistical validation of the theoretical framework, which provides insight regarding the role of institutional pressures on resources and their effects on the adoption of big data analytics-powered artificial intelligence, and how this affects sustainable manufacturing and

circular economy capabilities under the moderating effects of organizational flexibility and industry dynamism.

Keywords: Big data; Artificial intelligence; Industry 4.0; Circular economy; Sustainable manufacturing

1. Introduction

The business environment is dynamic and necessitates high quality decisions from strategic, operational and tactical perspectives, for staying competitive in the market (Dubey et al., 2020). Recently, large-scale data for decision making under fuzzy environments has drawn attention of industry professionals (Jabbour et al., 2019). However, dependency on data-driven manufacturing requires the configuration of tangible resources and development of workforce skills for sustainability and thereby need further research investigation (Dubey et al., 2019b). External pressures from government agencies including the Department of Trade and Industry (DTI) act as massive forces in this digital age. They direct firms to align and operate within the nation's digital strategy (Dubey et al., 2020). Institutional pressures guide a firm to operate within social boundaries and most countries have framed their individual digital strategies to drive digital programs within these social boundaries (Gerrikagoitia et al., 2019). These digital initiatives set specific goals and performance measures to improve manufacturing capabilities through innovation-driven production methods in this digital age (Li, 2018; Liu et al., 2020a). Furthermore, pressures from customers also force suppliers to adopt digital technologies to configure their resources and capabilities (Ancarani and Di Mauro, 2018; Dubey et al., 2019b). The literature indicates that institutional pressures have a positive influence on tangible resources (i.e. infrastructure, resource commitment, and resource availability) (Cavusoglu et al., 2015; Huang et al., 2016; Wang et al., 2018). The literature also indicates that institutional pressures have a constructive association with workforce skills (Mizruchi and Fein, 1999; Bacon and Hoque, 2005; Liang et al., 2007; Boon et al., 2009).

Resource based view theory explains that various assets are subsets of resources, and the bundling of resources helps develop capabilities. Some resources are vulnerable to easy imitation by competitors. Therefore, firms need to make prudent decisions and choose resources that are difficult for other organizations to copy. There are also complex resources, such as knowledge gained through practice. Workforce skills can be considered as tacit resources; these resources are not visible, as they are achieved through learning and practice

(Hart, 1995). In this digital era, knowledge of big data analytics (BDA) and artificial intelligence (AI) has proven to be a tacit resource, as successful application depends on workforce skills. These skills mainly include programming and data analytics skills. These resources can be considered socially complex resources, as they depend on a group of employees in coordination with a small number of experts who have in-depth knowledge to explain the entire process to the team. Tangible resources such as big data management infrastructure, technological resources (Hadoop for data processing, data visualization tools, and cloud based services) and basic resources (funds) are essential for BDA-AI project execution (Iqbal et al., 2018; Dubey et al., 2019b). Management can influence these capabilities by hiring experts or altering human resource policies (Molina-Azorín, 2014). In this study, the authors argue that external driving factors (institutional pressures) force firms to configure key resources (tangible resources and workforce skills) to develop BDA-AI capabilities and gain a competitive advantage (low costs, sustainable manufacturing, and material circularity). It would be interesting to look into the effect of institutional (coercive, normative, and mimetic) pressures on tangible resources and workforce skills in the adoption of BDA-AI. Hence,

RQ1: How do firms engaging in manufacturing activities adopt BDA-AI?

The rise in the global population is increasing demand for food, water, and energy and thus creating stress on natural resources (Del Borghi et al., 2019). The problem is growing due to non-sustainable production and utilization of resources. The “take-make-dispose” standards in the linear economy cause stress on natural environment, forcing manufacturers to search for sustainable alternatives (Julianelli et al., 2020). This problem can be effectively combated by shifting to a circular economy (CE) (Gao et al., 2020). Sustainable manufacturing practices (SMP) can drive the CE through the selection of eco-friendly materials for production and construction (Krolczyk et al., 2019; Ricciotti et al., 2020; Tan et al., 2020).

Data is a key driver in this fourth industrial revolution (I4.0) (Dubey et al., 2019a). I4.0 technologies can be leveraged to enhance research and developments related to smart manufacturing (Hennelly et al., 2020). Large data has proved extremely useful in I4.0 era and have the ability to unlock CE (Jabbour et al., 2020a). This has been confirmed by Pactwa et al. (2020) where they indicated that 3R methods are easily enabled by I4.0 technologies.

BDA has been found to improve the cost performance and operational performance of a firm (Dubey et al., 2019b). BDA and AI have a positive influence on the overall health of companies (Dubey et al., 2019c; Yasmin et al., 2020). Both CE and big data management has been discussed widely in disparate literature (Jabbor et al. 2019). One study that is worth mentioning is the work of Jabbor et al. (2019); where the research team attempted to integrate the CE (ReSOLVE model) and big data management; which further opened up newer research opportunities. To advance the literature, the effect of BDA-AI on SMP and CE capabilities needs further investigation (Abubakar et al., 2019; Grover et al., 2020; Nishant et al., 2020). Hence,

RQ2: What is the association between BDA-AI adoption and SMP and CE capabilities?

Organizational flexibility is the ability of organizations to perform their operations in a volatile business environment (Srinivasan and Swink, 2018). The attributes of organizational flexibility involve the ability to quickly adjust the structure of the organization and respond to the changing business environment. This ability also includes changing the organizational structure without having any negative impact on the quality of products or services. Organizational flexibility also helps a company adapt quickly to changing business situations and stay ahead of competitors (Dubey et al., 2019a). BDA and sustainable manufacturing are dependent on organizational structure (de Sousa Jabbour et al., 2018b). An analysis of the automotive industry reveals that enhanced organizational performance in dynamic situations is achieved when managers' use advanced digital technologies, such as BDA and AI (Bag et al., 2020b; Dubey et al., 2020). In less dynamic situations, the need for information to make fast decisions may not be as evident (Melville et al., 2007). The literature indicates that the use of ICT increases when the dynamics in the business environment increase (Melville et al., 2007). However, there is limited research available in this area demonstrating the moderating effect between the adoption of BDA-AI, SMP and CE capabilities. Hence,

RQ3: How do these motivating factors (institutional pressures and resources), affect SMP and CE capabilities of manufacturing firms under the moderating effect of organizational flexibility and industry dynamism?

Based on the discussion provided above, the overall objective of this work is to examine how institutional forces shape tangible resources and skills in the development of BDA-AI and impact SMP and CE capabilities. The model of Dubey et al. (2019b) has been adapted in our study to further develop testable hypotheses. The model is practice oriented and has the ability to sense not only BDA-AI adoption-related problems, but also to address SMP and CE capability development issues that several organizations are facing at this time due to the varying degree of institutional forces and resources. The model can be useful to understand real problems and to help managers and policy makers develop appropriate action plans to meet their sustainable development targets. This research study attempted to undertake an empirical survey to gather primary data in South Africa. The data analysis has been done using the partial least squares structural equation modeling (PLS-SEM) method (Hair et al., 2011), and lastly conclusions has been drawn.

The rest of the sections are organized as follows: section 2 presents the theoretical background and research hypotheses, section 3 showcases the research design employed in this study, section 4 presents the results followed by section 5, which presents the discussion of the findings, and the final section outlines the conclusion of the study.

2. Theoretical background and hypothesis development

Big data has proven immensely useful in the operations management field, including forecasting, inventory, finance, sales, logistics and supply chain management, and risk analysis (Choi et al., 2018; Brinch et al., 2018; De Caigny et al., 2020; Kamble and Gunasekaran, 2020). The explosion of data has brought new opportunities for cities from design and management perspectives. The processing of big data combined with AI can enhance urbanization and sustainability (Iqbal et al., 2018; Allam and Dhunny, 2019).

An entrepreneurial orientation drives firms to utilize BDA-AI capabilities to improve operational performance (Dubey et al., 2020). AI can enable a system to assimilate data and gain knowledge from such data. The knowledge can be further used to accomplish certain objectives and jobs (Haenlein and Kaplan, 2019). The adoption of BDA drives AI applications in production. Sensor technologies and IoT on the shop floor can capture production-related big data. Remaining work time during production can be estimated with deep learning using big data (Fang et al., 2019). Big data technologies can be used for product lifecycle management (Liu et al., 2020b).

Zhou et al. (2019) indicated that BDA-AI can drive intelligent manufacturing. AI and big data have proven useful in smart entrepreneurship (Obschonka and Audretsch, 2020). Future organizations will be shaped by BDA-AI and firms will succeed in these dynamic times by utilizing AI-based metrics while safeguarding the human component (Sahota and Ashley, 2019). Yablonsky (2019) proposed a framework that companies can use to understand data-driven human-machine relationships while applying AI at various levels of data-driven automation maturity.

The bright side of BDA is the ability to provide rich insights for high quality decision making and to be able to change strategies accordingly in this volatile business environment. Descriptive data analytics enable the organization to sense the business context and predictive analytics help it to seize business opportunities (Van Rijmenam et al., 2019). Big data have the ability to change the supply chain design and the way companies manage the traditional supply chain (Waller and Fawcett, 2013). BDA-AI will open up sustainability opportunities in the production domain and enhance CE capabilities (Jabbour et al., 2019; Nobre and Tavares, 2017; Tseng et al., 2018). The next section presents the theoretical discussion followed by the testable hypotheses.

2.1. Role of institutional pressures and resources in the adoption of BDA-AI, SMP, and CE capabilities

Institutional theory works within the resilient dimensions of a social system. It covers the norms and policies that are set up as authoritative directives for social actions (Scott, 2004). Institutional theory has been used by previous researchers such as Kondra and Hinings (1998) for organizational diversity, Kostova et al. (2008) for multinational corporations, Zhu et al. (2013) in the field of green supply chain management; and Dubey et al. (2019b) for big data management.

Scott (2005; 2008) and Weerakkody et al. (2009) have discussed progress in institutional theory; and Powell and Colyvas (2008) further discussed the micro-foundations of institutional theory. The research team intended to establish that institutional pressures compel firms to obtain resources and furthermore configure them to aid in the adoption of BDA-AI (Dubey et al., 2019b).

Resource based view (RBV) theory articulates the relationship between resources, capabilities, and competitive advantage (Barney, 1996, 2001). The fundamentals of RBV suggest that firms must configure resources in such a way as to build capabilities to sustain a competitive advantage (Hart, 1995). On the other hand, they should not allow competitors to imitate these resources. The basic attributes of the resources are that they need to be valuable and not easily replicable. The value dimension of resources makes them more complex and exceptional. Such a set of resources facilitates capability building related to key business areas (e.g. technology, marketing, distribution, and operations). These capabilities ultimately determine the competitive advantage position of the firm. It is clear that the lowest unit from the RBV perspective is that of resources.

Workforce skills fall under the category of tacit resources. These resources are not visible, as they are achieved through continuous practice and improvements (Hart, 1995). In this digital era, knowledge of BDA and AI has proven to be a tacit resource, as its application depends on workforce skills. These skills mainly include programming and data analytics skills. These resources can be considered to be socially complex resources, as they depend on a group of employees in coordination with a small number of experts who have in-depth knowledge to explain the entire process to the team. Tangible resources such as big data management infrastructure, technological resources (Hadoop for data processing, data visualization tools, and cloud based services) (Soriano et al., 2012), and basic resources (funds) are essential for BDA-AI project execution (Iqbal et al., 2018; Dubey et al., 2019b). In the current study, the research team argues that external driving factors (institutional pressures) force firms to configure key resources (tangible resources and workforce skills) to develop BDA-AI capabilities and gain a competitive advantage (lowering costs, sustainable manufacturing and circularity). Ravichandran and Lertwongsatien (2002) worked in similar areas, and drawing upon RBV, explained that resources are an integral part of information systems and have the potential to impact firm performance. To summarize, while the effect of external forces has been drawn from institutional theory and the effect of resources on BDA-AI has been drawn from the RBV perspective to scrutinize the connections, a key gap exists in the literature. Literature point out that there are various external forces and resources and there is little research on their direct effects on BDA or the relationship between BDA-AI and SMP and CE capabilities. The objective of this study is to contribute to the growing body of big data and sustainability outcome research by extending the existing theories to fill the gap in the literature. Research team attempted to integrate and synthesize the BDA-AI, SMP, and CE literature to create a theoretical model that shows the relationship among institutional pressures, resources, BDA-AI, SMP, and the CE capabilities. Two moderating variables, namely organizational flexibility and industry dynamism were added, to examine their effects on the path “BDA-AI and SMP” and on the path “BDA-AI and CE capabilities”. Various published research works have reflected the integration of institutional theory and RBV theory (Oliver, 1997; Fernández-Alles and Valle-Cabrera, 2006; Auh and Menguc, 2009; Zhang and Dhaliwal, 2009; Webb et al., 2011; Zheng et al., 2013; Hughes et al., 2017; Takahashi and Sander, 2017; Dubey et al., 2019b) to develop and explain theoretical models. This theoretical model is illustrated in Figure 1 and the proposed relationships are discussed in the remaining part of this section.

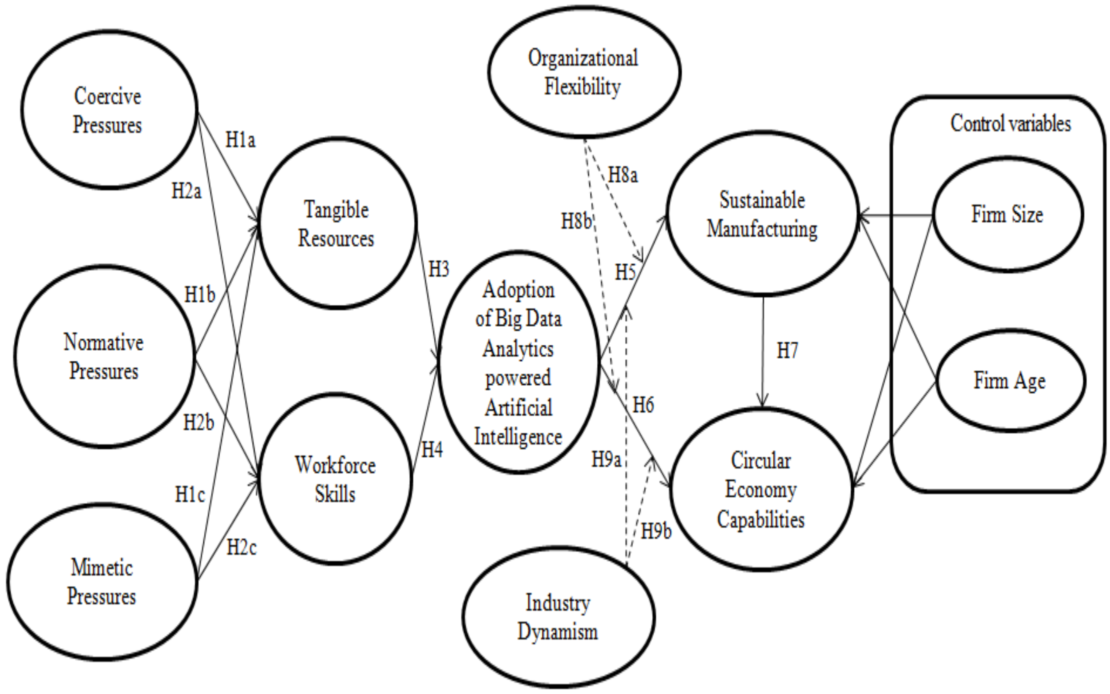

Figure 1. Theoretical model (Source: Adapted from Dubey et al., 2019b)

2.2. Hypothesis development

2.2.1. Institutional pressures and tangible resources

Firms need to take necessary actions after carefully considering the institutional pressures (Aydiner et al., 2019). There are three main types of institutional pressures: coercive pressures (CP), normative pressures (NP), and mimetic pressures (MP) (Dubey et al., 2019b). Pressures from the Government, DTI and other statutory bodies have enforced certain rules and regulations to protect data for safe usage. Data must be used within the framework of regulatory norms. Government intervention (such as tax cuts, public education, awareness creation programs, and pilot schemes), the drafting of suitable I4.0 standards and the creation of a technology-friendly environment are important for the sustainability of I4.0 projects (Lin et al., 2018). Furthermore, CP is found to bolster the development of tangible resources such as I4.0 infrastructure and further support companies with funding for I4.0 initiatives. Companies need to follow national level policies to acquire tangible resources (data connectivity, technology, and basic resources) for advanced technological applications (Dubey et al., 2019b). Therefore,

H1a: Coercive pressure has an affirmative association with tangible resources.

The literature indicates that pressures from suppliers and customers are responsible for developing certain tangible resources related to I4.0 (Man and Strandhagen, 2017). Suppliers and customers dealing with focal companies that lack suitable I4.0 infrastructure and other fundamental resources will not be able to do vertical and horizontal integration, which is an essential part in the implementation of I4.0 architecture and big data driven platform. (Telukdarie et al., 2018). Therefore, non-compliant businesses will lose technologically advanced suppliers and prospective customers, thus creating a disruption in the supply chain and face serious consequences. Therefore,

H1b: Normative pressures have a positive association with tangible resources.

The literature indicates that competitors practicing BDA-AI and gaining substantial benefits can also create pressure in the industry to focus on tangible resources related to BDA-AI (Lin et al., 2018). Competitors with tangible resources to develop BDA-AI capabilities can gain a competitive advantage and easily outperform other companies in the industry (Lopes de Sousa Jabbour et al., 2018a). Therefore,

H1c: Mimetic pressures have a positive association with tangible resources.

2.2.2. Institutional pressures and workforce skills

An I4.0 technological launch necessitates particular set of skills (Veile et al., 2019; Zangiacomi et al., 2020). The main data analytical techniques are statistics, machine learning, data mining, and optimization (Choi et al. 2018). Workforce skills include technological skills such as data analytics skills and soft skills (coordination, communication skills) (Wade and Hulland, 2004; Waller and Fawcett, 2013).

A skill shortage can negatively impact the industry and society (Dhamija and Bag, 2020). The Skills Development Act 97 of 1998 is a law enacted in South Africa that aims to enhance the skills and quality of life of the local workforce. It is important for South African firms to conform to Broad-Based Black Economic Empowerment (BBBEE) - code of good practice and create a pool of skilled human resources for economic growth. Without a valid BBBEE score, South African firms cannot do business with local companies or participate in government tenders. Skills are a key element in the BBBEE score and comprise 25 scoring points. Companies need to submit a workplace skill plan, annual training plan, and other statutory training plans to claim points under the skills category and avoid lowering their BBBEE level. Large companies are supposed to spend six percent of taxable earnings (tax on

skills development) and payroll on training (BEE online). Customers are willing to conduct business with suppliers with high BBBEE scores; and suppliers are under pressure to maintain the scores by investing in workforce skills development programs. Coercive pressures have a noteworthy effect on human skills in the South African context. Therefore,
H2a: Coercive pressures have an affirmative association with workforce skills.

The literature indicates that normative pressures positively influence workforce skills (Dubey et al., 2019b). As indicated previously, suppliers and customers are willing to do business with focal companies that have a high level of workforce skills that provide two advantages: first, high BBBEE scores and second, good quality workmanship that will provide a reason to stick with such businesses. Companies in South Africa are spending millions of Rands each year on training programs to upgrade workforce skills and satisfy both suppliers and customers. Therefore,
H2b: Normative pressures have an affirmative connection with workforce skills.

The literature indicates that mimetic pressures arising from competitor activities can influence workforce skills (Dubey et al., 2019b). Competitors' activities pressurize other firms in the adoption of innovative teaching methods which includes off-site and on-site training that aims to upgrade workforce skills to help employees adjust to I4.0. It is important that every firm prepare its workforce according to I4.0 requirements to remain competitive in the industry (Dhamija and Bag, 2020). Therefore,
H2c: Mimetic pressures have a positive association with workforce skills.

2.2.3. Tangible resources and adoption of big data analytics-powered artificial intelligence

Tangible resources (TR) including internet connection, infrastructure and fundamental resources are important to implement BDA-AI in the organization (Dubey et al., 2019b). Since large data is generated from different sources and the formats are different, therefore, necessary resources are important to manage and process the data for unlocking value (Katal et al., 2013). TR has a positive association with acceptance of BDA-AI (Dubey et al., 2019b, Dubey et al., 2020). Therefore,
H3: Tangible resources have an affirmative association with adoption of BDA-AI.

2.2.4. Workforce skills and adoption of big data analytics-powered artificial intelligence

Literature indicated that lack of workforce skills has prevented progress of I4.0 and firms therefore, need to overcome this barrier to progress in the adoption of digital technologies (Nam, 2019). The latest proficiency requirements will lead to alterations in work profiles. Maintenance of cyber-physical systems and programming are some of the skills which are gaining importance in this digital age. In addition, more emphasis must be given towards innovativeness and analytical thinking abilities (Jerman et al., 2020). Therefore, firms need to focus on learning and sharing of knowledge (Tortorella et al., 2020). Training on safety aspects of workers are important as automated machines/robots working in the shop floor is relatively new and can cause accidents (Ardanza et al., 2019). Hence,

H4: Workforce skills have an affirmative connection with adoption of BDA-AI.

2.2.5. Adoption of big data analytics-powered artificial intelligence and sustainable manufacturing

Artificial intelligence was introduced in the 1950s, and since then it has witnessed multiple ups and downs (Baryannis et al., 2019). The I4.0 era has witnessed substantial growth in computational aspects and an increase in big data accessibility, which has further renewed interest in the area of AI (Wamba et al., 2015; Baryannis et al., 2019). AI has proven its effectiveness in managing supply chain risks (Baryannis et al., 2019; Chien et al., 2020). Expert systems were popular up until 2000, and the rise of smart systems and data mining began during the 2010s. The building blocks of AI are comprised of: a) structured data; b) unstructured data, pre-processes; c) main processes; d) knowledge base; and e) information (natural language creation, image creation, and robotics) (Paschen et al., 2019).

Big data and high computing power have made AI more powerful in recent years (Duan et al., 2019). AI has returned to the business world with more opportunities in this I4.0 era (Lee et al., 2018; Dwivedi et al., 2019; Hughes et al., 2020; Pillai et al., 2020; Shareef et al., 2021). Selz (2020) rightfully pointed out that insights generated from the analysis of big data combined with AI will become the new control system in organizations. AI and machine learning provide various benefits such as lowering costs, enhancing quality and accelerating responsiveness (Aykroyd et al., 2019; Kim, 2019; Pettersen, 2019; Lee and Shin, 2020; Munoko et al., 2020). The pre-requisites for the adoption of AI include proper planning and a long-term AI vision, senior management support, human resources, technological infrastructure, customer support, and the right organizational strategy (Kim, 2019).

Big data is characterized by the 7V's: volume, variety, veracity, value, velocity, visualization, and variability. Companies face challenges in big data management, which can be overcome through the application of BDA methods such as descriptive analytics, predictive analytics, and prescriptive analytics (Sivarajah et al., 2017). Big data is generated from various sources (web, social media, ERP systems, and cloud platforms) in various formats (text, graphic, audio, and video clips) (Blazquez and Domenech, 2018). BDA-AI has brought on a digital revolution in the field of manufacturing (Yadegaridehkordi et al., 2018). The autonomous decision-making power of machines and distributed cooperation among agents results in a high level of flexibility on the shop floor (Wang et al., 2016). Therefore,

H5: Adoption of BDA-AI has a positive relationship with SMP.

2.2.6. Adoption of big data analytics-powered artificial intelligence and circular economy capabilities

The link between CE (regenerate, share, optimize, loop, virtualize, exchange) and big data (volume, variety, velocity and veracity) can be valuable for a firm (Jabbour et al., 2019). This relationship between these two concepts has been explained in detail by Jabbour et al. (2019). For instance, veracity of big data related to environmental impact assessment of inputs for production can be useful to select suitable sources of raw material that can enhance regeneration capabilities. Next, variety and velocity of sharing information is essential in developing robust CE strategies. Veracity also plays an important role in developing predictive maintenance plan depending on near and real time data.

Velocity, veracity and volume can change the loop's model in CE system. The characteristic of virtualize is essential to keep track of changing customer preferences and consumption patterns. Lastly, a variety of information is essential for replacing old processes with new processes that can unlock CE (Jabbour et al., 2019). AI has also proven useful in managing circular supply chain (Dhamija and Bag, 2020). Adoption of I4.0 technologies (big data analytics-powered AI) has a positive relationship with CE capabilities (Gupta et al., 2019). This is supported by several studies (Dubey et al., 2020; Carvalho et al., 2018; Lopes de Sousa Jabbour et al., 2018b; Fisher et al., 2018; Stock et al., 2018; Stock and Seliger, 2016; Theorin et al., 2017). Data driven recycling, reducing, and reusing solutions in manufacturing are key components for achieving circularity capabilities (Tseng et al., 2018). Advanced I4.0 technologies can improve the application of CE by unlocking the circularity of resources in the system (Lopes de Sousa Jabbour et al., 2018a). AI, service, and policy frameworks are found to be strong enablers that can integrate I4.0 and CE (Rajput and Singh, 2019). Nascimento et al. (2019) also demonstrated that I4.0 technologies involving big data and AI support CE practices. Therefore,

H6: Adoption of BDA-AI has a positive relationship with CE capabilities.

2.2.7. Sustainable manufacturing practices and circular economy capabilities

SMP is found to guide CE capabilities (Zeng et al., 2017). SM can be achieved in three ways. The first method is the use of environmentally-friendly materials to make goods that can be re-circulated in the system at the end of their useful life (Ferasso et al., 2020). The second method is the use of advanced technology to enhance process efficiency and reduce waste by eliminating defects in the production process. The third method is the use of pollution free technologies to reduce harmful effects in the factory and its surroundings (Zeng et al., 2017). SMP helps to develop CE capabilities by adopting methods like recover, recycle, repurpose, remanufacture, refurbish, repair, re-use, reduce, rethink, and refuse (Morseletto, 2020; Bag et al., 2021). Therefore,

H7: SMP have a positive association with CE capabilities.

2.2.8. Moderating effect of organizational flexibility

Organizational flexibility is the ability of organizations to run their business in a volatile business environment (Srinivasan and Swink, 2018). The attributes of organizational flexibility involve the ability to quickly adjust organizational structures and respond to changing business environments. This ability also includes modifying the organizational structure without there being any negative effects on the quality of products or services. Organizational flexibility also helps firms adapt more easily to changing business situations and stay ahead of competitors (Dubey et al., 2019a). BDA and SMP are dependent on management factors such as organizational structure (Soriano, 2010; Lopes de Sousa Jabbour et al., 2018b). Therefore, the greater the organizational flexibility, the greater the adoption of BDA-AI and enhanced SMP. Based on the preceding discussion, we argue that the enabling effects of the adoption of BDA-AI and SMP are positively moderated by organizational flexibility. Therefore,

H8a: The higher (or lower) the level of organizational flexibility, the higher (or lower) the enabling effects of BDA-AI on SMP.

Successful adoption of BDA-AI and CE capabilities is dependent on organizational flexibility, as the ability of organizations to change their structure and processes quickly can contribute to the successful application of advanced technologies to enhance CE capabilities (Garcia-Muiña et al., 2018; Bag and Pretorius, 2020). Based on the preceding discussion, we argue that the enabling effects of the adoption of BDA-AI and CE capabilities are positively moderated by organizational flexibility. Therefore,

H8b: The higher (or lower) the level of organizational flexibility, the higher (or lower) the enabling effects of BDA-AI on CE capabilities.

2.2.9. Moderating effect of industry dynamism

Industry dynamism arises due to constant changes in technological, socio-political, and environmental aspects in the region in which the business operates (Melville et al., 2007). Industry dynamism is difficult to forecast and this ambiguity makes it difficult for managers to make decisions. During turbulent situations, managers need to make quick decisions (Melville et al., 2007) to prevent products or services from becoming obsolete (Dubey et al., 2020). In a dynamic business environment, the preferences of customers change and are further reflected in purchasing behavior. Organizations need to adopt new operating processes and technologies and continuously put new products and innovative services on the market (Dubey et al., 2019a). Today's customers are more inclined to purchase green products that are environment friendly (Ali et al., 2019). Therefore, organizations turn to sustainable manufacturing with the aim of achieving sustainable development goals (SDG) (Bag and Pretorius, 2020). The literature indicates that I4.0 can enable SMP and CE capabilities (Lopes de Sousa Jabbour et al., 2018b; Bag et al., 2021). An analysis of the automotive industry reveals that enhanced organizational performance in dynamic situations is achieved when managers' use advanced ICT such as BDA and AI (Bag et al., 2020b; Dubey et al., 2020). In less dynamic situations, the need for information to make fast decisions may not be as evident (Melville et al., 2007). The literature indicates that the use of ICT increases as the dynamics in the business environment increase (Melville et al., 2007). We argue that in a dynamic business environment, organizations need more information to configure resources for SMP. Therefore, BDA-powered AI is activated at a higher level when the business environment is more dynamic. Therefore, H9a: The higher (or lower) the level of industry dynamism, the higher (or lower) the enabling effects of BDA-AI on SMP.

Similarly, we also argue that in a dynamic business environment, organizations need more information to configure resources and develop capabilities for the CE. Therefore, BDA-powered AI is activated on a higher level when the business environment is more dynamic. The enabling effects of BDA-powered AI and CE capabilities are found to be positively moderated by industry dynamism. Thus,

H9b: The higher (or lower) the level of industry dynamism, the higher (or lower) the enabling effects of BDA-AI on CE capabilities.

3. Research methods

3.1. Sampling strategy

The research team selected 219 companies from the database of the National Association of Automotive Component and Allied Manufacturers (NAACAM) and the National Association of Automobile Manufacturers in South Africa (NAAMSA) and e-mails were sent to two potential respondents working in managerial role from each company. South Africa is an emerging economy and there has been a great deal of activity related to BDA-AI technological applications recently in the automotive sector. Automotive and related component manufacturing accounted for 33 percent of this country's production output in 2016. This sector also contributed to approximately 7.4% of GDP and is considered an important sector for economic growth. It is therefore suitable for this research study.

3.2. Instrument development

The instrument was developed based on a five-point Likert scale design. A multiple-item, 5-point Likert-type scale (1="Strongly Disagree"; 2="Disagree"; 3="Neutral"; 4="Agree"; 5="Strongly Agree") was used. This type of 5-point scale is common and has been used by researchers in the past (e.g. Dwivedi et al., 2013; Kapoor et al., 2014; Shareef et al., 2016; 2017; Sharma and Sharma, 2019; Bag et al., 2020ab) in business management research. The scale used in this study was adapted from previous research studies. Constructs such as coercive pressures (three items), normative pressures (two items), and mimetic pressures (two items) were considered based on the work of Zeng et al. (2017). Tangible resources (eight items) and workforce skills (seven items) were considered based on the work of Dubey et al.

(2019b). Adoption of big data analytics-powered AI was considered based on the work of Carvalho et al. (2018) and Dubey et al. (2020) and consists of ten items. Sustainable manufacturing (eight items) and circular economy capabilities (ten items) were considered based on the work of Zeng et al. (2017). There were two moderating variables: organizational flexibility (five items) adapted from the study of Srinivasan and Swink (2018) and Dubey et al. (2019a) and industry dynamism (four items) adapted from the study of Dubey et al. (2020). The details are presented in Table A.1. A pilot survey was done among forty executives from the automotive sector and the questionnaire wording related to institutional pressures and circular economy capabilities was modified based on the feedback received from them, but no items were eliminated from the questionnaire.

3.3. Data collection

The data was collected in two phases. The initial online survey participation request was sent in early 2020 and the research team did follow-up after three weeks. The research team received 57 completed responses before the reminder was sent. After the reminder was sent, the research team received 162 completed questionnaires. No half-filled questionnaires were returned, as the electronic system did not allow for incomplete submissions. The rate of response in this study was approximately 51%, which is acceptable in empirical research studies in the field of business management. The characteristics of the respondents are presented in Table 1. The findings show that the maximum number of responses was received from senior managers. The findings also indicate that the majority of responses were received from people with more than 20 years of experience in the automotive industry. Moreover, the bulk of reply were received from people associated with organizations that have been operating in South Africa for over 20 years and with turnover of more than 50 million ZAR. Therefore, we are confident that the data quality is good and suitable for this study.

Table. 1

Summary of respondents

Details	Category	Number of Participants	Participants (%)
Designation	General Manager	34	0.16
	Senior Manager	110	0.50

	Manager	35	0.16
	Junior Manager	40	0.18
Experience (Years)	Above 20	136	0,.62
	10 to 20	79	0.36
	Below 10	4	0,02
Nature of Business Activities	OEMs' catering to vehicle assembly plants	110	0.50
	Manufacturers and dealers of OE and accessories	65	0.30
	Manufacturers of replacement items	26	0.12
	Manufacturers of allied products	8	0.04
	Dealers of associated/support items	10	0.05
Age of the Firm (Years)	>20	75	0.34
	15 to 20	78	0.36
	10 to 14	47	0.21
	5 to 9	15	0.07
	Below 5	4	0.02
Annual Turnover (ZAR)	< R10 million	0	0.00
	<R50 million	87	0.40
	>R50 million	132	0.60

3.4. Non-response bias test

The primary data was received in two phases. The early wave (57 responses) and the late wave (162 responses) were compared using Levene's test to check for non-response bias (Armstrong and Overton, 1977).

The research team tested to see if the distribution of the variables differed based on these waves. SPSS software was used to compare means and perform the analysis by selecting one-way ANOVA and then run a “homogeneity of variance” test. The wave was the factoring variable and the research team wanted the results (*p* value) to be non-significant. If the *p* value was below 0.05, research team could reject the null hypothesis and conclude that there was no equality of variance. If they were non-significant, it meant they were not different. The research team found that none of the values were significant, which means there was no difference between the waves. Therefore, Leven’s test established the equality of variances in the samples (homogeneity of variance) ($p > 0.5$ as shown in Table 2) (Martin and Bridgmon, 2012).

Table. 2

Levene Statistic

	Levene Statistic	df1	df2	Sig.
CP	3.450	1	217	.065
NP	1.865	1	217	.173
MP	.096	1	217	.758
TR	3.186	1	217	.076
WS	6.189	1	217	.014
BDAI	2.153	1	217	.144
SMP	4.226	1	217	.041
CEC	.993	1	217	.320
ORF	.939	1	217	.334
IND	.970	1	217	.376

4. Results

To test the hypotheses, the research team used PLS-SEM based WarpPLS version 6.0 software.

4.1. Measurement model

The measurement model was assessed before the research team examined the results of the WarpPLS. APC, ARS and AARS were statistically significant and there was no problem with the model. AVIF and AFVIF values were within the acceptable range (see Table 3). High AVIF and AFVIF values are not desirable and high values can occur if various latent variables with similar meanings are involved in the same model measuring the same underlying construct. The Tenenhaus goodness-of-fit value shows a large fit and suggests that the explanatory power of the model is high (Kock, 2012).

Table. 3

Model fit and quality indices parameters

Model fit and quality indices	Values (Source: WarpPLS output)
Average path coefficient (APC)	0.198
Average R-squared (ARS)	0.118
Average adjusted R-squared (AARS)	0.106
Average block VIF (AVIF)	1.315
Average full collinearity VIF (AFVIF)	2.766
Tenenhaus GoF (GoF)	0.250

To check the presence of any endogeneity problems, the research team checked SPR, RSCR, SSR, and NLBCDR as per the guidelines of Kock (2015) and found them to be within acceptable limits. The SPR was 0.800 (acceptable if ≥ 0.7, ideally = 1), which indicates the absence of Sympson's paradox in the model. The RSCR was found to be 0.793 (acceptable if ≥ 0.9, ideally = 1). The SSR should be greater than or equal to 0.7 and the results indicate a value of 0.933, i.e. that ninety three percent of the paths in the model are free from statistical suppression. Finally, the NLBCDR value was checked and found to be 0.933, which indicates that in at least ninety three percent of path-related instances in a model, the support for the reversed hypothesized direction of causality is weak or low (see Table 4).

Table. 4

Causality assessment indices

Causality assessment indices	Values (Threshold Values if any) (Source: WarpPLS output)
Sympson's paradox ratio (SPR)	0.800
R-squared contribution ratio (RSCR)	0.793
Statistical suppression ratio (SSR)	0.933
Nonlinear bivariate causality direction ratio (NLBCDR)	0.933

4.2. Common method bias test

The results show that full collinearity VIFs are 3.3 or lower, which proves the existence of no multicollinearity in the model. This indicates the absence of common method bias (Kock and Lynn, 2012). The results for factor loadings show that the values are more than 0.50 and within acceptable limits (Hair et al., 1998). Scale composite reliability was found to be above 0.70 and acceptable. The AVEs were found to be above 0.50 and satisfy the discriminant validity criteria (Fornell and Larcker, 1981; Nunnally and Bernstein, 1994). The research team also checked the correlations among latent variables with respect to square roots of AVEs (see Table 5) to satisfy the discriminant validity criteria, i.e. all the square roots of AVEs are greater than the correlation values for that particular latent variable (Fornell and Larcker, 1981). The values present on the diagonal in brackets are greater than any other values present above or below those values in the same column.

Table. 5

Discriminant validity check

	CP	NP	MP	TR	WS	BDAI	SM	CEC	ORF	IND
CP	(0.846)									
NP	0.436	(0.849)								
MP	0.270	0.264	(0.815)							
TR	0.103	0.162	0.121	(0.689)						
WS	0.292	0.294	0.054	0.117	(0.448)					
BDAI	0.242	0.239	0.035	0.272	0.258	(0.639)				
SM	-0.001	-0.011	-0.017	0.307	-0.005	0.238	(0.749)			
CEC	0.818	0.640	0.592	0.249	0.426	0.329	0.043	(0.601)		
ORF	-0.135	-0.068	-0.099	-0.076	-0.025	0.051	0.099	-0.090	(1.000)	
IND	-0.096	-0.024	-0.074	0.007	0.014	0.020	0.072	-0.072	0.372	(0.742)

The findings from the examination of the hypotheses are presented in Figure 2. The findings indicate a value of 18% for explaining CE capabilities. The path coefficient (beta coefficient) values and their corresponding *p* values are presented in figure 2. The outcome of the hypothesis examination demonstrate that there is a positive association between CP →TR (β=0.21); CP →WS (β=0.13); NP →WS (β=0.12); MP →TR (β=0.14); TR →BDA-AI (β=0.35); WS →BDA-AI (β=0.17); BDA-AI →SMP (β=0.44); BDA-AI →CEC (β=0.52) and SMP →CEC (β=0.14). The moderating effect of organizational flexibility (β=0.14) and industry dynamism (β=0.13) on the path BDA-AI→CEC is supported. The cut-off value for determining statistical significance is considered to be 5% as per previous research studies (Bag, 2020 a,b) performed in the business management field. All hypotheses except 1b, 2c, 8a, and 9a were supported. The research team also considered the effect of control variables such as company size and age, which were found to be non-significant.

The R^2 value of the endogenous construct was checked and the value was found to be fairly strong (18%) (Chin, 1998). The research team further checked the f^2 values for CEC and they were higher than the threshold value of 0.00 (Dubey et al., 2020).

Stone-Geiser's value of Q^2 was finally checked to estimate the explanatory power of the endogenous constructs. The Q^2 values were as follows: for TR (0.072), for WS (0.210), for BDA-AI (0.178), for SMP (0.194), and for CEC (0.230). All these Q^2 values were found to be higher than 0.00 and the predictability of the model is therefore acceptable.

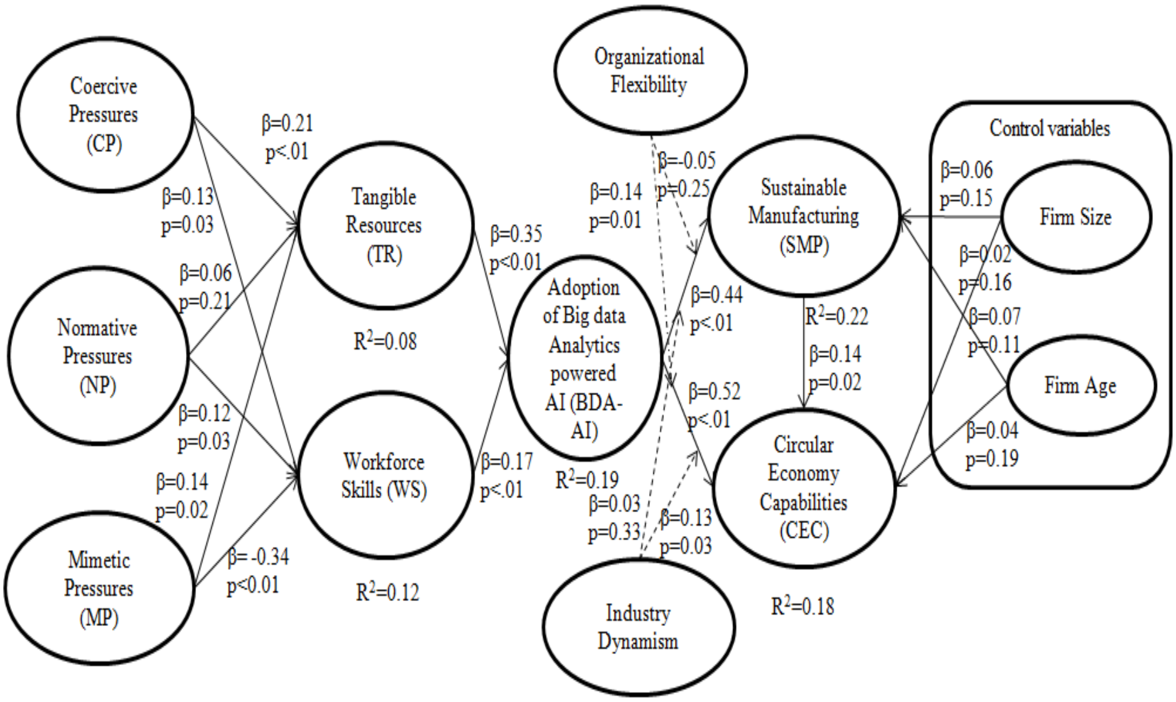

Figure 2. Model after SEM (WarpPLS result)

5. Discussion

The path "coercive pressures and tangible resources" showed a significant relationship. The path "mimetic pressures and tangible resources" showed a significant relationship. However, the effect of coercive pressures on tangible resources was found to be greater than that of mimetic pressures. The path "coercive pressures and workforce skills" showed a positive relationship. The path "normative pressures and workforce skills" showed a positive relationship. However, the effect of coercive pressures on workforce skills was found to be greater than that of normative pressures. The path "tangible resources and BDA-AI" showed a positive association. The path "workforce skills and BDA-AI" showed a positive association. However, the effect of tangible resources on BDA-AI was found to be very strong compared to the effect of workforce skills on BDA-AI.

Dubey et al. (2019b) performed a study in which they tested the effect of coercive pressures, normative pressures, and mimetic pressures on tangible resources and human skills. Their research findings showed that coercive pressures do not have a significant effect on human skills. However, our research findings show that coercive pressures have a significant effect on human skills and these coercive pressures were found to be the strongest institutional driver in the South African context. Skill shortages in South Africa have forced the government to implement instruments such as BBBEE to create a pool of skilled human resources for the growth of the economy. Without a valid BBBEE score, South African firms cannot do business with local private or public companies. Therefore, every firm is pressured to invest in skill development training every year. Our results show that normative pressures do not have a significant effect on tangible resources and mimetic pressures do not have a significant effect on workforce skills. However, both of these hypotheses were supported in the study by Dubey et al. (2019b), which was conducted in Indian industries. The reason may be due to coercive pressures that already impact resources by preventing businesses from engaging in any kind of unfair usage of resources. Also, coercive pressures have an impact on workforce skills, and every company in South Africa is focusing on this area due to the fear of losing business due to a low BBBEE score. We therefore think that mimetic pressures on workforce skills are not having an impact in this case.

The path "BDA-AI and SMP" was found to be significant. The path "BDA-AI and CE capabilities" was found to be significant. However, the effect of BDA-AI on CE capabilities was found to be stronger compared to the effect of BDA-AI on SMP.

Finally, the path "SMP and CE capabilities" was found to be significant.

The adoption of Industry 4.0 technologies has a positive association with CE capabilities. This is supported by several studies (e.g. Carvalho *et al*., 2018; Lopes de Sousa Jabbour *et al*., 2018b; Dubey *et al*., 2019c; Fisher *et al.*, 2018; Gupta et al., 2019; Stock *et al*., 2018; Stock and Seliger, 2016; Theorin et al., 2017). However, our study has extended the knowledge base by using selective I4.0 technology (BDA-AI) and further extended the work of Dubey et al. (2019b).

Another interesting finding which emerged from our study was that the enabling effect of BDA-AI and CE capabilities is positively moderated by organizational flexibility and industry dynamism. This is supported by past studies such as those by Srinivasan and Swink (2018) and Dubey et al. (2019a). However, our findings did not show any positive moderating effect either of these variables on the path "BDA-AI and SMP".

5.1. Theoretical contributions

Institutional pressures have a very important role in South Africa in terms of digital technology adoption and sustainability practices. Our study suggests that institutional pressures are guiding automotive and allied component manufacturing firms to work within social boundaries by creating a balance between key assets such as human capital and resources to further enable digital technological adoption. Coercive pressures are very strong in South Africa, followed by mimetic pressures, which means that competition is very fierce in the South African marketplace. Normative pressures are fairly strong in this country when it comes to the effect on tangible resources and workforce skills. These mechanisms can be successfully explained with the help of institutional theory. Furthermore, another element that had a strong impact in our theoretical model is resources as explained using the popular RBV theory. The key resources for BDA-AI adoption are first tangible resources and second workforce skills. This study offers a better picture of institutional pressures and resources that are essential for the adoption of BDA-AI in South African automotive and allied manufacturing firms. One of the key contributions of this study points towards the CE, and we therefore looked into the competitive CE literature and compared our findings with some of the notable studies in the field of CE, as presented below.

Jabbour and Santos (2008 a,b) highlighted the importance of human resources in developing sustainable businesses. Our findings highlight that workforce (human) skills are positively associated with BDA-AI adoption and further it is positively associated with CE capabilities which is a new link that we have established in our study.

In addition, Jabbour et al. (2020c) indicated that big data can be useful to enhance sustainable supply chains. Our study however highlighted that BDA-AI adoption is positively associated with sustainable manufacturing which is also a new link that we have established in this study.

Jabbour et al. (2020b) conducted research in the emerging economy of Brazil and found that the regulatory mechanisms are different compared to other countries. Their study found that stakeholders influence CE adoption and further CE adoption enhances sustainability performance. Our study was also conducted in an emerging economy. However, our results indicate that institutional forces influence resources for BDA-AI adoption which further influence SMP, and CE capabilities. These are also new links that we have established in our study.

The impact of CE business models on operations management was investigated by Lopes de Sousa Jabbour et al. (2019). The ReSOLVE model was combined with big data to provide an integrated framework. This framework provides the managers with the ability to anticipate the need to develop CE-related capabilities. Another study by Jabbour et al. (2019) proposed an integrative framework to improve the knowledge of large scale data-CE nexus. The framework focused on relationships that can be important for firm’s stakeholders and further proposed twelve research propositions. The contribution of the study of Jabbour et al. (2019)

lies in the design of integrative framework relating- the main stakeholders (supplier, customer and manufacturer) of CE, the ReSOLVE model and the four Vs of big data management which was indeed a novel contribution to the CE literature. The study of Jabbour et al. (2019) is related to stakeholders; however, we have supported our study with institutional theory and RBV theory. The study of Jabbour et al. (2019) considered big data; however, we have considered big data analytics powered artificial intelligence construct in our study which is a very powerful element in this digital era. Compared to the competitive CE literature, our study contributes to the CE literature by establishing that institutional pressures play a key role in configuring tangible resources and workforce skills for adopting BDA-AI, and further sustainable manufacturing practices is necessary to develop CE capabilities.

5.2. Managerial implications

The key takeaway points are as follows:

Focus on tangible resources: Both regulatory pressures and competitors are forcing automotive and allied product manufacturing companies in South Africa to acquire key resources and configure tangible resources. The South African Government is putting pressure on these firms through “BBBEE” and the “Skills Development Act” to improve workforce skills. In addition, suppliers and customers are forcing this sector to upgrade workforce skills to prevent a drop in BBBEE scores. Managers must focus on tangible resources such as BDA-AI infrastructure, digital platform, technologies, and basic resources to execute BDA and AI projects.

Focus on workforce skills: It is also essential that managers focus on developing workforce skills through proper training programs to keep them abreast of the latest BDA-AI programming techniques. Since BDA-AI plays a key role in enhancing sustainable manufacturing practices and building CE capabilities, managers need to put more emphasis on this area. They need to make the necessary arrangements and adopt benchmark practices to contribute to economic growth in South Africa. Although SMP have gained popularity in South Africa, more focus is still needed on building CE capabilities by adopting CE strategies.

Focus on adoption of BDA-AI to enhance SMP and CE capabilities: Sustainable manufacturing aims to select special materials to build products using special tools and clean production methods. Renewable energy sources such as solar or wind energy should be used in SMP. Environmentally-friendly designs must become more important and environmental factors need to be considered when selecting business partners. More attention must be given to innovative approaches to find recycling solutions.

CE uses 3R methods such as reduce, reuse, and recycle in which reverse logistics and the supply chain network design play a very important role. Supply chain disruptions may cause production losses, financial issues, or relationship issues with customers.

Many firms are still following decades old practices of cutting costs and minimizing raw material stock levels as well as eliminating flexibility during such processes, which can make the firm more vulnerable in the CE. I4.0 technologies have proved to be a boon in the field of operations management by providing firms with enhanced visibility and resilience. BDA-AI technologies are able to gather voluminous data generated from various sources and help machines make autonomous decisions, thus bringing greater flexibility to the manufacturing process and enhancing circularity capabilities. There will be less chance of disruption in the supply network and enhanced collaboration and agility in the supply chain. Institutional pressures are forcing companies to upgrade worker skills and also cover data privacy and security aspects, which directly contributes to the adoption of BDA-AI.

However, the maintenance of BDA-AI applications requires constant review and intervention by senior management in order to use advanced analytical and data visualization methods for better decision making. BDA-AI adoption can offer advantages to manufacturers involved in CE by providing more recycling options and thus enhancing the life cycle of resources, lowering waste and quickly adjusting to more efficient processes.

5.3. Limitations and future research directions

This study was conducted in the emerging economy of South Africa, where digitalisation is at a nascent stage. The social conditions where the automotive and allied sectors operate in South Africa are different from any other country. Therefore, the nature of institutional pressures is different here compared to any other emerging economy such as China, India, or Brazil. Furthermore, the skill level in South Africa is low and the Government of South Africa has undertaken various initiatives to upgrade these skills to prepare for digitalisation. The scenario may be different in other countries and we therefore caution future researchers that the findings must be interpreted in light of the abovementioned limitations. The model can be tested further in a country where coercive pressures are strong, to further generalize the results. Our study acts as a stepping stone towards I4.0 (big data-powered AI) technological application, sustainable manufacturing and circular economy.

6. Conclusion

This study is a novel attempt to scrutinize the effect of institutional pressures on tangible resources and workforce skills for BDA-AI adoption and to understand the impact of BDA-AI adoption on SMP and CE capabilities. The research findings show the unique pathways such as the positive relationship between BDA-AI adoption and SMP and CE capabilities. The study considered samples from automotive component and allied product manufacturers in South Africa. This is the only sector that has progressed significantly in terms of digitalisation compared to other sectors. Moreover, this sector is seriously considering environmental and social aspects when making manufacturing-related decisions. This is all possible due to the cooperation of the Government, suppliers, and customers acting together to meet SDG. The digital process is essential to further advance circularity capabilities. Although South Africa has implemented digital goals and South African Universities such as University of Johannesburg and the DTI are helping local businesses set up feasible digital models, more momentum is required from internal organizational leaders to meet project deadlines.

The findings indicate that coercive pressures and mimetic pressures are positively associated with tangible resources. Furthermore, coercive pressures and normative pressures indicate a positive association with workforce skills. Tangible resources and workforce skills indicate a positive association with BDA-AI adoption. BDA-AI adoption was found to have a positive association with SMP and CE capabilities and finally, SMP were found to have a positive association with CE capabilities. Another interesting finding that emerged from our study was that the enabling effect of BDA-AI and CE capabilities is positively moderated by organizational flexibility and industry dynamism. Our study provides theoretically-guided information for managers to enhance BDA-AI adoption and further improve SMP and CE capabilities.

Appendix

Table A.1: Operationalisation of constructs

Constructs	Code	Items	Adapted from
Coercive Pressures (CP)	CP1	Laws and regulations have provided direction on safeguarding environment and cleaner manufacturing	Zeng et al. (2017)

	CP2	Government impose penalty on environmental damage and resource wastages	
	CP3	The pollution control department continuously monitors the environmental pollution level of firms	
Normative Pressures (NP)	NP1	Customers highly respect the management considerations adopted by suppliers related to the society and environment	
	NP2	Strong social responsibility are appreciated by customers and attract collaborations	
Mimetic Pressures (MP)	MP1	Corporate management promote cleaner manufacturing and sustainability	
	MP2	Companies follow the laws and regulations of safeguarding surroundings during manufacturing operations	
Tangible Resources (TR)	FP1	Company have the right of use to large data sets	Dubey et al. (2019b)
	FP2	Company have the ability to perform integration of large data arising from internal sources	
	FP3	Company have the ability to perform integration of large data arising from external sources	
	FP4	Company use Hadoop for processing large data sets	
	FP5	Company use data visualization tools to gain insight from large data sets	
	FP6	Company use cloud-based services for management of large data sets	
	FP7	Company have budgeted funds for BDA-AI project execution	
	FP8	We have set realistic timeline to achieve desired results from BDA-AI	
Workforce Skills (WS)	WS1	We offer BDA-AI related training to our employees	Dubey et al. (2019b)
	WS2	We recruit new employees who have good exposure to BDA-AI	
	WS3	Our BDA staff has the right skills to do the job successfully	
	WS4	Our BDA staff has the right education	
	WS5	Our BDA staff holds suitable years of experience in big data environment	
	WS6	Our BDA managers have strong understanding of business	

	WS7	Our BDA managers are able to coordinate effectively with all supply chain actors	
Adoption of Big data analytics powered by AI (BDA-AI)	BDAI1	BDA-AI is used in the company for enhancing decision making power	Carvalho et al. (2018); Dubey et al. (2020)
	BDAI2	Using BDA-AI our company can easily integrate information from different data sources	
	BDAI3	We routinely use data visualization techniques to assist users or decision makers to understand complex information	
	BDAI4	Our dashboards give us the ability to decompose information to help root cause analysis and focus on continuous improvement	
	BDAI5	Longer machine life cycle, decrease in industrial waste, and faster adaptation towards more efficient processes by leveraging BDA-AI	
	BDAI6	Company has optimised resource usage and utilise assets in a better manner by leveraging BDA-AI	
	BDAI7	Recycling options has increased by leveraging BDA-AI	
	BDAI8	Better adaptation to demand curves, better use of resources, faster response to energy supply changes	
	BDAI9	BDA-AI project is lead by experts and everyone follow the timelines strictly	
	BDAI10	BDA-AI project goals and are reviewed regularly based on the dynamic business environment	
Sustainable Manufacturing Practices (SMP)	SMP1	Company use alternate source of energy in manufacturing process	Zeng et al. (2017)
	SMP2	Environmentally friendly production technology and manufacturing processes are emphasized	
	SMP3	Company emphasises on environmentally friendly product design	
	SMP4	The development and implementation of rules and regulations in environmental protection are evaluated when selecting dealers	

	SMP5	Company considers its ability to provide environmentally conscious products and packaging when selecting dealers	
	SMP6	Company sells waste and used materials to other firms	
	SMP7	Company designs/optimises ways to recycle waste materials and spare parts	
	SMP8	A waste product recycling, classification, and processing centre is established	
Circular Economy Capabilities (CEC)	CEC1	Company is dedicated to reducing the unit product manual input	Zeng et al. (2017)
	CEC2	Company is dedicated to reducing the consumption of raw materials and energy	
	CEC3	Company initiatively enhances the energy efficiency of production equipment	
	CEC4	Product packaging materials are used repeatedly	
	CEC5	Equipment cleaning materials are used repeatedly	
	CEC6	Leftover material is used repeatedly to manufacture other products	
	CEC7	Waste produced in the manufacturing process is recycled	
	CEC8	Waste products from consumers is recycled	
	CEC9	Recycling waste and garbage is reprocessed	
	CEC10	Waste and garbage is used after reprocessing to manufacture new products	
Organizational Flexibility (ORF)	ORF1	Company can speedily change the organizational structure to respond to changing business conditions	Srinivasan and Swink (2018); Dubey et al. (2019a)
	ORF2	Company can cost effectively change the organizational structure to respond to changing business conditions	
	ORF3	Company can change the organizational structure without negatively impacting service quality	
	ORF4	Current organization structure enables to adapt to changing business conditions	
	ORF5	Our company is more flexible than our competitors in changing our organizational structure	
Industry Dynamism (ID)	IND1	Our product and services become outdated quickly	Dubey et al. (2020)
	IND2	Our organization continuously introduces new products and services	
	IND3	Our organization introduces new operating	

		processes	
	IND4	The customers taste and preferences in our industry changes fast	

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