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Examining the role of virtue ethics and big data in enhancing viable, sustainable, and digital supply chain performance

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ABSTRACT

In the real world of practice, data-driven supply chains have gained huge popularity in recent years. This has led operations and supply management researchers to the focus on the role of advanced information and technology, including big data. Literature highlights that the use of big data can enhance business performance. Nonetheless, big data is analyzed by humans and a lack of virtue ethics could lead to disastrous consequences (erroneous decision-making can stem from bad data analysis resulting in not only huge business losses but also deterioration of relationships with suppliers and customers in the supply chain). To address the calls of previous researchers, this study utilizes the Ethical Theory of Organizing framework and Stakeholder theory to develop the theoretical model and further examine the relationships. The samples are drawn from the manufacturing industry. Hypothesis testing is executed through covariance-based structural equation modeling and finally, the conclusions are drawn. The findings of this work provide a more nuanced understanding of virtue ethics and big data implications, thereby answering the important questions of "why" and "how" data-driven green and lean practices increase the stakeholders' trust and enhance viable, sustainable, and digital supply chain performance.

1. Introduction

The world is witnessing the changes caused by consecutive industrial revolutions, each contributing to the progress of mankind (Bag and Pretorius, 2020). Nonetheless, the risks that each industrial revolution brings should never be ignored (Soh and Connolly, 2021). As the world transitions into the fourth industrial revolution, changes in the business landscape are being seen, brought by emerging technologies such as big data analytics and artificial intelligence (Choi et al., 2018; Bag et al., 2021a,b). These systems are extremely useful for managing information in long and complex supply chains (SC) (Choi and Chen, 2021), where information, product, and financial flows are crucial. Information flows from the upstream SC to the downstream SC and vice-versa. The information must be managed properly for making key SC decisions (ranging from strategic to operational level). Firms can capture large datasets (also called big data) thanks to the advancements in wireless sensor networks, Internet of Things (IoT), Industrial Internet of Things (IIoT) and the development of cyber-physical systems (CPS) (Kang et al., 2016; Choi et al., 2021). Making decisions in SC has grown challenging due to the increased supply and demand uncertainties in this post-pandemic era; yet big data technologies can be useful in making SC decisions (Sheng et al., 2021).

Big data is characterized by its volume, variety, velocity, veracity, and value (Wamba et al., 2017). The increasing number and complexity of datasets are in part due to the rapid growth of mobile data traffic, cloud computing traffic, and the rapid development of information and communication technologies. Global data generation is expected to reach >180 zettabytes by 2025. The rise in demand, owing to the COVID-19 pandemic, caused the growth to be larger than projected, as more individuals worked from home and frequently used home

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entertainment alternatives.[1]

Big data analytics (BDA) is related to working, processing, and analyzing large datasets which are mainly unstructured in nature (Wamba et al., 2017). The importance of big data technologies has is reflected in the high number of related publications in recent years. This prior research mostly highlighted the antecedents of BDA including the resources and capabilities that are important to enhance firm performance (Akter et al., 2016; Wamba et al., 2017; Mikalef et al., 2019). In other studies, previous authors argued that BDA plays a critical role in driving operations and supply chain sustainability (Raut et al., 2019; Bag et al., 2020). The data analysis process is very dynamic and iterative, however, and it necessitates the presence of a human in the loop, giving rise to the necessity of provenance management, which is rarely taught (Mellody, 2014).

It has been highlighted, however, that BDA can have disastrous consequences unless the person managing the big data is virtuous in nature. Data analysts have complete command and control over data sets, and they are the ones who make arguments based on the findings. As a result, misinterpretation of outcomes from the analysis of massive data sets can lead to poor business decisions and significant losses. There may be other risks as well, such as data analysts sharing secret company information with competitors. This raises concerns about accountability and governance structures. We must not disregard the growing significance of a framework of attitudes and practices that can help people make ethically sound judgments and behaviors in a data-driven environment.[2] Ethical behavior refers to the positive and conscious attitude of big data analytics personnel toward the business core principles, culture, and climate in organizations that are crucial for the success of the organization (Grodzinsky, 2017; Herschel and Miori, 2017; Someh et al., 2019). So far, this area of attention has lacked focus and current literature fails to clearly explain the “how” and “why” questions related to virtue ethics and ethical behavior of BDA experts in firms. Since the lack of virtue ethics causes privacy issues for others, it is, therefore, worth examining these relationships.

We are in an era where importance is being given to the achievement of sustainable development goals (SDGs) (El-Haddadeh et al., 2021). With the advancement of information and communication technologies, organizations are inclined toward the usage of big data-driven lean and green techniques and tools that aim to reduce wastage and enhance environmental performance in organizations (Oliveira et al., 2018; El-Haddadeh et al., 2021). However, past studies did not investigate the direct/indirect influence of virtue ethics on data-driven green and lean practices. Hence, we formulate our first research question:

RQ1. What is the relationship between virtue ethics, ethical behavior of BDA personnel, and data-driven green and lean practices; and how are they related to each other?

The work of Dubey et al. (2019) considered control orientation as a moderating variable to examine its effect on the path of big data analytics and social performance/environmental performance; however, the moderating effect of internal control effectiveness lacked attention in the big data literature. Hunziker (2017) claimed that internal control allows businesses to warrant accurate reporting, adherence to applicable laws and standards, and the efficiency and success of their business procedures. Internal control effectiveness is a broad term that refers to a set of procedures that encompasses the complete spectrum of methods, procedures, and controls used by businesses to achieve their goals and ensure that the organization’s data is processed securely (Hunziker, 2017). Therefore, strong/poor internal control effectiveness (complexity of internal control systems, competence, internal communications, and monitoring) can increase/decrease the influence of virtue ethics on ethical behavior but to date, there have been few empirical contributions that conceptualize and experimentally investigate the moderating role of the effectiveness of internal control. Hence, we formulate our second research question:

RQ2. How does internal control effectiveness play a moderating role in the relationships between virtue ethics, and ethical behavior of BDA personnel, while the ethical behavior of big data analytics personnel plays a mediating effect on the path of virtue ethics and data-driven green and lean practices in manufacturing industries?

The process of comprehending big data and its implications for organizational, technical, and human aspects is a complex procedure. Big data efficiently deploy technology and engage expertise to store and analyze data and create value (Surbakti et al., 2020). Big data enables modern corporate management to develop innovative ideas that increase operational excellence, financial returns, and customer experience (Ghasemaghaei and Calic, 2020). Zheng et al. (2020) highlighted the importance of big data in Chinese e-commerce enterprises’ distribution systems. In turn, supply chain management (SCM) is becoming increasingly important to the success of e-commerce businesses. For instance, the logistics distribution mechanism that is chosen has a direct impact on the performance of e-commerce businesses (Zheng et al., 2020).

It is perhaps surprising that very few articles have examined the relationship between BDA and Lean, Green practices in the operations and supply chain management field (Belhadi et al., 2020; Gupta et al., 2020; Belhadi et al., 2021a; Raut et al., 2021). From our research, we have not been able to discover any previous studies that have examined the influence of virtue ethics on data-driven lean and green practices; furthermore, the literature lacks work that clearly explains the influence of data-driven lean and green practices on shareholders’ trust and final impact on viable, sustainable, and digital supply chain (VSDSC) performance. Hence, this study aims to address the third research question:

RQ3. How can firms enhance VSDSC performance in the context of data-driven lean and green practices in manufacturing industries?

In this digitalized era, big data is critical for data-driven information management (Kushwaha et al., 2021). Big data analytics is a promising technique for analyzing marketing from a consumer’s perspective. Big data provides an automated intelligent system that assists management in decision-making (Wang and Wang, 2020). However, managing and controlling big data access is a serious challenge for the business globally. Various countries are confronted with significant obstacles in enacting data security and accessibility legislation (Iqbal et al., 2020). While dealing with big data, privacy and security are major concerns. Several studies have been conducted to investigate the positive aspects of big data, but ethical issues associated with big data have been ignored, necessitating this study to investigate the ethical perspective of big data. We aim to fill up the gap in the existing literature by examining the influence of virtue ethics and ethical behavior of big data analyst personnel.

The study used the lens of the “Ethical Theory of Organizing” proposed by Yazdani and Murad (2015) to develop the theoretical framework and the arguments were further supported by “Virtue Ethics theory” (Shanahan and Hyman, 2003; Herschel and Miori, 2017) and “Stakeholder theory” (de Camargo Fiorini et al., 2018; Gupta et al., 2019; Someh et al., 2019; C. Wang et al., 2020). The theoretical discussion and model development are presented in the next section.

Our contribution to this study- First, we conceptualized virtue ethics as a necessary component of addressing ethical challenges in big data, particularly in terms of how it can influence BDA experts’ ethical behavior. Second, we conceptualized that virtue ethics is critical for

[1] Statista report, Volume of data/information created, captured, copied, and consumed worldwide from 2010 to 2025, Retrieved from https://www.statista.com/statistics/871513/worldwide-data-created/#statisticContainer on 22.11.2021.

[2] https://minerva-access.unimelb.edu.au/bitstream/handle/11343/227494/BigData-%20Can%20Virtue%20Ethics%20Play%20a%20Role%20unimelb.pdf?sequence=1&isAllowed=y.

implementing lean and green practices, as research shows that a lack of virtue ethics can lead to greenwashing and false claims about promoting environmentally friendly products and services. Greenwashing is influenced by leadership styles reflecting obedience to authority and further moderated by ethical incentives (Blome et al., 2017). Therefore, managers must focus on virtue ethics to drive lean and green practices; in doing so, it will increase the trust level of stakeholders, and corporate image and finally it will improve VSDC performance.

The rest of the sections are organized as follows. Literature on big data is presented in Section 2. The theoretical model is discussed in Section 3. The study is important since it triggered debate related to ethics and big data. Section 3 is followed by research methods where we have discussed the empirical research design adopted in this study. The data analysis is presented in Section 5. The implications for research and practice are presented in Section 6. The final section provides limitations and future research directions.

2. Literature review

2.1. Big data and sustainable operations and supply chain management

Big data is transforming the way of doing business. It revolutionizes business processing and has been used in a variety of fields. Information technology was identified as one of the nine fundamental features of a long-term company plan in the work of Goni et al. (2021). Organizational resources require big data and predictive analytics capabilities to enhance the organizational performance of the firm (Jeble et al., 2018; Li et al., 2021). Big data enable 3V (variety, velocity, and volume) to enhance the efficiency of operation and supply chain management (Lamba and Singh, 2017), however, the use of big data in supply chain performance is still in its infancy (Lamba and Singh, 2017). Data-driven supply chain management leads to information exchange, coordination, activity integration, and responsiveness. These factors have a further significant positive impact on the financial performance of the firm (Yu et al., 2018). The resource-based theory proved that big data analytics (BDA) helps to build SC ambidexterity capability and further enhances superior organization performance (Wamba et al., 2020; Mikalef et al., 2019). BDA is used in SCM to overcome barriers and more efficiently utilize resources. (Kazancoglu et al., 2021). The capabilities and resources of SC and operational performance are enhanced by big data and predictive analysis (BDPA). Understanding BDPA assimilation as a competence requires a resource-based perspective (Gunasekaran et al., 2017). BDPA enables flexibility and capacities by integrating the SC (Yu et al., 2021). The theory of diffusion analytics has explained that BDA has the potential to revolutionize SC practices (Arunachalam et al., 2018).

Big data helps supply chain operations to be more sustainable and make better decisions (Lopes de Sousa Jabbour et al., 2018; Pereira et al., 2021). It enables supply chains to optimize their transportation management, forecasting, inventory management, and human capital management (Inamdar et al., 2020; Raut et al., 2021). SCM is improved by BDA, which also reduces uncertainty (Benzidia et al., 2021). Data-driven sustainability practices have an impact on the integration of big data technologies with organizational processes, which enhances the association between internal and external performance and has a favorable impact on the sustainable performance of organizations (Singh and El-Kassar, 2019). Big data is one of the most crucial components of sustainable SCM since data-driven practices increases performance by providing economic benefits, environmental benefits, and operational risk reduction (Tseng et al., 2019).

Gunasekaran et al. (2018) developed a framework to investigate the importance of big data and business analytics on lean and green manufacturing using qualitative data from four companies. In the context of resource-based view theory, BDA can improve lean and green manufacturing, and environmental performance (Belhadi et al., 2020; Zekhnini et al., 2021). Raut et al. (2021) have identified seven elements having an impact on BDA i.e., lean techniques, social practices, environmental practices, organizational practices, supply chain practices, financial practices, and total quality management which leads to sustainable supply chain performance. Dubey et al. (2018) used dynamic capabilities view in their study and conclude that big data enhance collaboration, predictive analysis, and alliance creation which increases the sustainable development goals and improves the performance of the SC.

According to Ren et al. (2019), BDA is one of the most important technologies in sustainable smart manufacturing. It uses a huge amount of data to effectively remove the hidden pattern, which in turn assists the decision-maker (Ren et al., 2019). The complementary relationship between BDA and lean practices improves business performance in a dynamic environment (Gupta et al., 2020). The efficiency of big data applications is determined by the virtue ethics of the big data analytics personnel (Herschel and Miori, 2017) yet the impact of virtue ethics and big data on the improvement of the digital SC has not been incorporated in previous studies. It is, therefore, necessary to examine the relationship between big data and digital SCM, which is critical for the organization's virtue ethics and long-term viability.

2.2. Ethical issues in processing and managing big data

Big data generated on digital platforms are influencing organization decisions, human interaction, and the working environment because of the rapidly accelerated growth of information and communication technologies. Transforming big data into real-world information is important to assist decision-makers in the fields of economics, e-commerce, market intelligence, public safety, and smart health systems. The ethical issue of big data has become a major concern and must be taken into consideration while working with large datasets (Chang, 2021; Andrew and Baker, 2021).

Chang (2021) proposed a framework for dealing with the ethical challenges surrounding big data in smart cities. They suggested that people must become aware of the importance of privacy and become cautious while sharing personal information. They also advocated for lawmakers to reform regulations surrounding disruptive technology, particularly big data. The policymakers are in a dilemma in making appropriate cyber policy to protect systems from cyber-attack while the bureaucracy is a barrier to advancing the use and integration of big data.[3] The consideration of various factors while making privacy-related laws is a complex issue (Chatterjee et al., 2021). The threat of stolen data being misused is a high-priority ethical concern for policymakers. Examples of such fraud include the sale of credit card information,[4] leaked personal information from Facebook[5] and AirIndia,[6] inadequate data mechanisms in financial institutions,[7] transparent use of blockchain technology,[8] and the ability to mislead and misuse data for financial gain.[9]

These scams raise the question mark on the security of big data in

[3] https://www.weforum.org/agenda/2021/01/top-cybersecurity-challenges-of-2021/.

[4] Retrieved from https://www.csoonline.com/article/3541148/the-biggest-data-breaches-in-india.html on 1.02.2022.

[5] Retrieved from https://economictimes.indiatimes.com/tech/technology/personal-details-of-6-1-million-facebook-users-in-india-leaked-online/articleshow/81916959.cms on 1.02.2022.

[6] Retrieved from https://www.91mobiles.com/hub/5-major-data-breaches-india-2021/ on 1.02.2022.

[7] Retrieved from https://analyticsindiamag.com/pnb-scam-can-data-analytics-clean-mess/ on 1.02.2022.

[8] Retrieved from https://analyticsindiamag.com/pnb-scam-can-data-analytics-clean-mess/ on 1.02.2022.

[9] Retrieved from https://economictimes.indiatimes.com/satyam-was-india-incs-biggest-fraud-it-wont-be-the-last/articleshow/4943248.cms?from=mdr on 1.02.2022.

various industries. The organization's long-term success is contingent on the confidentiality of its sensitive data. For the long-term development of all stakeholders, big data should be used ethically. The manufacturing business is likewise being affected by big data, which is changing traditional factories into smart factories. The importance of a data-driven SC in improving efficiency cannot be overstated. As such, it is necessary to investigate the importance of virtue ethics and big data in the long-term performance of SCM, which is critical for the expansion of the manufacturing industry.

3. Theoretical underpinning and model development

3.1. Ethical theory of organizing

According to Yazdani and Murad (2015), modern ethical theory in organization is founded on a scientific approach and empirical investigation. The Ethical Theory of Organizing can be used to create an internal organization framework that demonstrates the relationship between constructs and variables. Business ethics and moral behavior are critical to the organization's long-term viability, which leads to increased financial success (Yazdani and Murad, 2015). This theory contributes to the establishment of an organization's corporate social responsibility, human dignity, and cooperation. This supports an organization's management in attaining the organizational goal (Albareda and Sison, 2020). Without trust, an organization's goal will not be fulfilled. Trust is an essential component that functions as a bond in both the firm's internal and external environments. Trust strengthens the organization's ethical standard and is a critical component of ethical organizational theory (Yazdani and Murad, 2015). Trust and virtue ethics have become the main pillars in modern ethical organizational theory (Yazdani and Murad, 2015). They proposed a conceptual model (pp. 409) where they linked "Ethical Climate Antecedents", "Organizational Practices" and "Consequences". Virtue ethics has been shown as an important antecedent in the model. Kind-heartedness, harmony, respect for others, hard work, humanness, righteousness, wisdom, justice, compassion, equity, humility, repelling evil with good, avoiding arrogance, greed and lust, and patience (all pursuing "higher goods") are the core of the ethical climate envisioned through the ethical theory of the firm (Yazdani and Murad, 2015). The model also proposed ethical training and ethics audits under organizational practices that can help a firm to realize the antecedents. As a result, improved moral efficacy, moral courage, moral identity, and OCB at all levels of an organization are the first significant outcomes of the model proposed by Yazdani and Murad (2015).

3.2. Virtue ethics theory

According to Shanahan and Hyman (2003), business ethics is influenced by two types of moral standards: deontology and teleology. The deontological concept holds that behavior is either right or wrong by virtue. The principle of teleology investigates the outcomes of actions. Both principles should be considered to improve the ethical standard of the organization (Shanahan and Hyman, 2003). Virtue ethics is required to improve business ethics within an organization. Shanahan and Hyman (2003) identified six important components of virtue ethics i.e., respect, piety, empathy, incorruptibility, reliability, and protestant work ethics. According to Herschel and Miori (2017), virtue ethics focuses on moral values rather than duties and responsibilities. Virtue ethics is needed to improve an individual's moral ethics. Virtue ethics is classified into two parts i.e., moral virtue ethics and intellectual virtue ethics (Herschel and Miori, 2017). Moral virtue ethics are based on daily habits and dispositions that develop through time because of repeated activity. Moral values-driven people are constantly seeking to improve their ethics by focusing on justice, honesty, loyalty, and charity. This leads to an increase in the performance of the organization (Herschel and Miori, 2017).

3.3. Stakeholder theory

The stakeholder theory was developed to remedy the flaws of the traditional view, which was based on increasing shareholder wealth. Stakeholder theory focuses on improving a firm's social performance rather than its financial performance (Friedman and Miles, 2002). This theory emphasizes meeting the needs of all stakeholders. In this theory, a stakeholder is an individual or group that has an impact on or is impacted by a company (Pirson and Malhotra, 2011). Stakeholders are mainly classified into three types: internal, external, and distal. Employees, the organization's management, and executive staff are all internal stakeholders (Someh et al., 2019). External stakeholders include suppliers, creditors, shareholders, and the local community. Distal stakeholders comprise consumers, competitors, labor unions, and government regulatory authorities. The stakeholder theory emphasizes virtue ethics and big data to improve the company's performance (Gupta et al., 2019). Wang et al. (2021) used stakeholders' theory to determine the impact of BDA on SCM performance, which improves business efficiency. In this study, we used stakeholder theory, in combination with virtue ethics theory to develop our model.

3.4. Model building

The Ethical Theory of Organizing model proposed by Yazdani and Murad (2015) argued that ethical climate antecedent influences organizational practices which follows the consequences that ultimately shape the firm performance. We referred to the Ethical Theory of Organizing and argued that ethical climate antecedent (Virtue ethics) influences organizational practices (data-driven lean and green practices) which follow the consequences (stakeholders' trust, and firm's reputation) that ultimately shape the firm performance (viable, sustainable, and digital SC performance). This is in line with the argument of Herschel and Miori (2017), that big data permits firms to quickly gather, process, and interpret data into useful information, it can also provide access to data that can compromise privacy aspects. Big data are not humans; however, big data is processed by humans, and this may happen intentionally or accidentally. According to virtue ethics theory virtue is a character trait that is well embedded in its holder which makes the human virtuous. Therefore, the person working with the big data must be virtuous as their actions may impact the privacy of others. Dishonesty and greed are dangerous and therefore the character and intentions of big data scientists and employees who deal with data must have strong ethical character. Ethical theories aid in answering how the personality and ethics of big data scientists can impact performance (Moorthy et al., 2015; Weston, 2016; Grodzinsky, 2017).

We argue that virtue ethics is important for data-driven lean and green practices in firms. The virtue ethics quality guides the employees in the organization to focus on data-driven waste minimization and clean production processes (Zekhnini et al., 2021) that enhance the green image, which in turn increases the trust level of shareholders in the firm. The shareholders comprising of employees, suppliers, customers, and shareholders of the firm will gain confidence and begin to believe that the firm can perform well in the market and outperform what can be measured on the viable, sustainable, and digital SC performance metrics (Zekhnini et al., 2021). This is supported by the stakeholder theory that focuses on the interconnected relationships between the firm and its stakeholders; and the firm should create value for all its stakeholders (Friedman and Miles, 2002). We claim that data-driven green and lean practices are adding value for all stakeholders and increasing corporate image and ultimately leading to sustainability (Fineman and Clarke, 1996).

We have also argued that internal control effectiveness (complexity, competence, communication monitoring) moderates the relationship between virtue ethics and the ethical behavior of big data analytics experts while the ethical behavior of big data analytics personnel acts as a mediating role. Literature indicates that Dubey et al. (2019)

considered control orientation as a moderating variable to examine its effect on the path of big data analytics and social performance/environmental performance. Based on the preceding discussion we present the research hypotheses below.

3.5. Hypotheses development

3.5.1. Virtue ethics and the ethical behavior of big data analytics personnel

Individual characteristics such as loyalty, compassion, openness, and fairness influence virtue ethics. People with virtuous traits are expected to behave ethically and correctly. Empathy, fairness, respect, and honesty are instilled in employees of a company whose moral standards are influenced by virtue ethics (Shanahan and Hyman, 2003; Adam and Bull, 2008; Grodzinsky, 2017). The theory of virtue ethics puts a strong emphasis on the overall significance of moral virtue and character. The traditional normative theory of virtue ethics is built on the notion of moral virtue (Shanahan and Hyman, 2003). According to Alzola et al. (2020), the normative theory is the best explanation for the prominence of virtue ethics in business ethics. It supports the creation of a positive corporate climate within the organization by encouraging loyalty and honesty. Alzola et al. (2020) found a link between the normative status of social relationships, the growth of excellent characters inside organizations, and virtue ethics, all of which are necessary for good leadership. Virtue ethics leads to the ethical behavior of BDA personnel. In big data-driven social transformation, the ethical issue has become a top priority for organizations and regulatory bodies. Data analytics regulation theory emphasizes data privacy and security so that it is not utilized for unethical purposes (Inamdar et al., 2020; Chang, 2021). As per Alfawaz et al. (2010), data security is influenced by the social environment, technological enhancement, regulation, and self-interest. The classification theory is the most effective way to determine which individuals in a company can access sensitive data for analytics purposes based on their ethical behavior. It has been argued that virtue ethics has a positive relationship with the ethical behavior of big data analytics personnel. Hence, we hypothesize

H1. Virtue ethics has a positive relationship with the ethical behavior of BDA personnel.

3.5.2. Virtue ethics and data-driven lean and green practices

Garcia-Ruiz and Rodriguez-Lluesma (2014) previously built on MacIntyre's goods-virtues-practices-institutions system and Beabout's concept of domain-relative practices. They contend that when engaging in utilization exercises, specialists may seek goods internal to practices, further their personal stories, and contribute to the betterment of their communities, hence creating excellences that idealize themselves both as buyers and moral specialists. In the past, many firms resorted to greenwashing and false claims concerning environmental and social responsibility practices. Therefore, it is crucial to create a perspective on moral character as the fundamental component of ethical thinking using the theory of virtue ethics. The management's moral standards are strengthened via virtue ethics (Herschel and Miori, 2017). If the data analyst managers do not have the basic virtue ethics characteristics, then greenwashing will continue and secondly, the firm will fail to adopt data-driven lean and green practices. Hence, virtue ethics attributes such as empathy, protestant work ethic, piety, respect, reliability, and incorruptibility are essential for data-driven lean and green practices (Zekhnini et al., 2021). Therefore, we hypothesize

H2. Virtue ethics has a positive relationship with data-driven lean and green practices.

3.5.3. Ethical behavior of big data analytics personnel and data-driven lean and green practices

Hughes and Ball (2020) broaden the scope of their research beyond technology and describe the social implications of BDA in the workplace. They applied social theory and grounded theory to explain that the deployment of BDA which depends upon ethical practices. Big data analytics should increase the value of an organization's technical and non-technical employees by developing good organizational culture. The social application of BDA improves ethical behaviors among employees, resulting in ethical behavior among BDA personnel (Grodzinsky, 2017; Herschel and Miori, 2017; Hughes and Ball, 2020). The organization's ethical theory interprets the ethical behavior of the workforce. The ethical theory of organizations, enabled by BDA, explains the values that an organization has for its stakeholders as well as its employees (Breidbach and Maglio, 2020). Yu et al. (2018) conducted a study on Chinese manufacturing companies and found that BDA in SCM provides a competitive edge. The study of Yu et al. (2018) broadened the scope of resource-based theory by demonstrating that data-driven SC capabilities improve business performance. Data-driven SCM improves demand forecasting and supply planning capabilities, resulting in lean and green practices to avoid waste (Yu et al., 2018; Lai et al., 2018). BDA becomes crucial for the decision-making process (Choi and Chen, 2021). Unless the big data analyst demonstrates ethical behavior, it will impact the quality of information, and not only that there are high risks related to the leaking of data to competitors for some monetary gains. Hence, we hypothesize

H3. Ethical behavior of BDA personnel has a positive relationship with data-driven lean and green practices.

3.5.4. Moderating effect of internal control effectiveness

Hunziker (2017) used organizational theory to develop the construct of internal control effectiveness. Internal control effectiveness is a broad term that refers to a set of procedures that encompasses the complete spectrum of methods, procedures, and controls used by businesses to achieve their goals and ensure that the organization's data is processed securely (Hunziker, 2017). According to organizational theory, using BDA improves an organization's efficiency which develops a trust culture in the firm (Adam and Bull, 2008; Lamba and Singh, 2017), furthermore, the use of big data improves control efficiency's capabilities and effectiveness. Establishing ethical organizational discipline utilizing the organization's ethical theory improves the efficacy and efficiency of the employees. The ethical theory of organizations places a strong focus on ethical employee behavior standards as they are essential to building organizational discipline (Albareda and Sison, 2020). BDA improves transparency within a business, encouraging management to enhance their ethical standards. Big data-driven management of an organization enables the employees to get accurate and timely information which enhances the efficiency of the organization (Mikalef et al., 2019; Akter et al., 2020; Li et al., 2021).

Resource-based theory suggests that big data analytics optimize the internal resources of an organization. Ethical standards are also a valuable part of an organization's internal resources (Akter et al., 2020). A high ethical standard could be achieved by the virtue ethics of the employees. Virtue ethics leads to ethical behavior in BDA which could be improved/lowered by increasing/decreasing internal control effectiveness. As such, we hypothesize that internal control effectiveness exerts a moderating role between virtue ethics and ethical behavior of BDA personnel.

BDA evaluates and interprets an organization's internal operations and can assist management decisions in reducing or eliminating waste (Yu et al., 2018; Roßmann et al., 2018; Ren et al., 2019). The elimination of waste can be significantly improved through the adoption of data-driven lean and green practices within the firm (Yu et al., 2018). BDA personnel play a critical role in any organization because they deal with sensitive information. They must have the capabilities to perform challenging tasks. The theory of reasoned action can explain an individual's behavior and intentions toward job performance (Alfawaz et al., 2010; Raut et al., 2019). The importance of employees' intentions while dealing with BDA, which is crucial in information security, has been determined using the theory of planned behavior, which is an advanced version of the theory of reasoned action (Alfawaz et al., 2010). The optimal involvement of BDA personnel, as well as their ethics, are therefore critical determinants of any organization's performance. The social theoretical concept should therefore be operationalized to improve the ethical standards of big data analytics personnel (Hughes and Ball, 2020). Hence, we hypothesize

H4. Internal control effectiveness exerts a moderating effect on the path of virtue ethics and the ethical behavior of BDA personnel while the ethical behavior of BDA personnel plays a mediating effect on the path of virtue ethics and data-driven green and lean practices.

3.5.5. Data-driven green and lean practices and stakeholders' trust

Organizations are adopting lean and green practices to improve business efficiency, cut production costs, and optimize business strategy. The goal of lean and green practices is to improve the quality of an organization's system to increase its efficiency (Belhadi et al., 2020; Raut et al., 2021). Data-driven green and lean practices provide better decision-making abilities that can benefit all SC actors leading to a higher level of trust among stakeholders. The stakeholder theory supports comprehending and putting into practice a transparent relationship between the stakeholders. This notion encourages the participants to aggregate and manage their resources (Pirson and Malhotra, 2011). The most effective way to identify the capabilities of data-driven green and lean practices within firms is to use the resource-based view theory. BDA improves an organization's quality management, which has a substantial impact on green and lean practices (Belhadi et al., 2020). Data-driven green and lean practices increase the revenue of the organization which enhances its value. The greater value of the firms leads to stakeholder trust (Blome et al., 2017; Someh et al., 2019). The existing theories could be expanded to explain the influence of data-driven green and lean practices on business value, increasing stakeholder trust (Blome et al., 2017). Hence, data-driven green and lean practices have a significant positive impact on stakeholder trust. Hence, we hypothesize

H5. Data-driven green and lean practices have a positive relationship with increased stakeholder trust.

3.5.6. Data-driven green and lean practices and firms' reputation

A company's reputation is vital to achieving organizational success in developing a competitive advantage. A company must identify the important elements that contribute to its reputation to sustain and improve it (Walsh and Beatty, 2007; Walsh et al., 2009). Walsh and Beatty (2007) identified seven important factors of a firm's reputation i. e., quality of product and services, good employer, financially leverage company, target orientation, responsibility toward the environment, strong company, and reliability. Walsh et al. (2009) used signaling theory to explain the relationship between a firm's reputation and loyalty which leads to trust and satisfaction. The company's ethical standards determine its reputation. The primary factor in determining competence and a company's reputation is ethical standards. The management of the organization can improve and enhance its reputation with the assistance of the ethical organization theory (Hitt et al., 2021). The reputation of a firm is a strategic indicator of its value enhancement. A good reputation is an intangible resource of the company which provides a sustainable competitive advantage (Kwon and Lee, 2019; Lee and Kwon, 2019). In the era of Industry 4.0, environmental sustainability is an important factor in a firm's reputation. Environment sustainability could be achieved by adopting lean and green practices (Kwon et al., 2021). Big data further enhance the effectiveness and efficiency of lean and green practices which strengthens the reputation of the firms. Hence, data-driven lean and green practices have a positive relationship with firm's reputation. We therefore hypothesize.

H6. Data-driven green and lean practices have a positive relationship with firm's reputation.

3.5.7. Stakeholders' trust and viable, sustainable, and digital supply chain performance

Digital SC performance has become increasingly important in the manufacturing sector. Digital technologies enable the firm to maintain SC performance sustainability in an uncertain environment (Yu et al., 2018; Zekhnini et al., 2021). The performance of the digital supply chain assists management in overcoming issues such as natural disasters, supply changes, volatile economies, and so on. The covid-19 pandemic has proved the importance of viable, sustainable, and digital SC performance (Zekhnini et al., 2021). During the covid-19 pandemic, digital technology assisted in maintaining a sustainable SC for essential commodities led to the enhancement of stakeholder trust. The success of a digital supply chain is determined by its integration with lean and green techniques, as well as its long-term viability (Zekhnini et al., 2021). The stakeholder theory explains the significance of the stakeholders' relationships. This theory presented a comprehensive view of the stakeholders' roles and helped foster trust among them (Aboramadan et al., 2021). The stakeholders in SC are shareholders, suppliers, intermediaries, and customers. Trust among stakeholders' acts as a strong force that motivates organizations to make continuous efforts toward the improvement of digital and sustainable SC performance. Lack of trust results in more openness and transparency, stakeholders' share resources and more buy-in ultimately improves the SC performance. So, we can say that stakeholder trust could be increased by viable, sustainable, and digital supply chain performance. Hence, increased stakeholder trust has a positive relationship with viable, sustainable, and digital SC performance. Therefore, we hypothesize

H7. Increased stakeholder trust has a positive relationship with viable, sustainable, and digital SC performance.

3.5.8. Firm reputation and viable, sustainable, and digital SC performance

The firm reputation is crucial in enhancing its worth and attracting the attention of its stakeholders. Companies that place a great emphasis on environmental sustainability can maintain a positive reputation, which increases the firm's financial performance (Lee and Kwon, 2019). According to stakeholder theory, it is the prime responsibility of stakeholders like employees, suppliers, customers, and investors to facilitate the sustainability of the organization which leads to the firm's reputation (Gupta et al., 2019; Someh et al., 2019; Pham and Tran, 2020). According to the stakeholder theory, an organization should involve all its stakeholders in reputation-building endeavors (Someh et al., 2019). Emerging technologies have a significant impact on SCM (Saha et al., 2022). Digitalization has become an integral part of an organization's operations. The digitalization process improves the lean system's performance by increasing the value of the organization. Digital SC performance reduces operational costs; maximizes the use of existing resources, and improves the performance of the extended supply chain. This leads to the enhancement of corporate reputation (Zekhnini et al., 2021). This shows the positive relationship between firms' reputations and viable, sustainable, and green SC performance. Hence, an increased firm's reputation has a positive impact on viable, sustainable, and green SC performance. We therefore hypothesize

H8. Increased firm reputation has a positive relationship with viable, sustainable, and digital SC performance.

Based on the preceding discussion the theoretical model is presented in Fig. 1.

4. Research method

In this study, we considered a deductive research approach, whereby the objective is to examine the concepts identified from a prescribed theory by using primary data. As such, a survey instrument was designed for data collection. Following the operationalization of constructs, an online questionnaire was created and distributed as per the defined

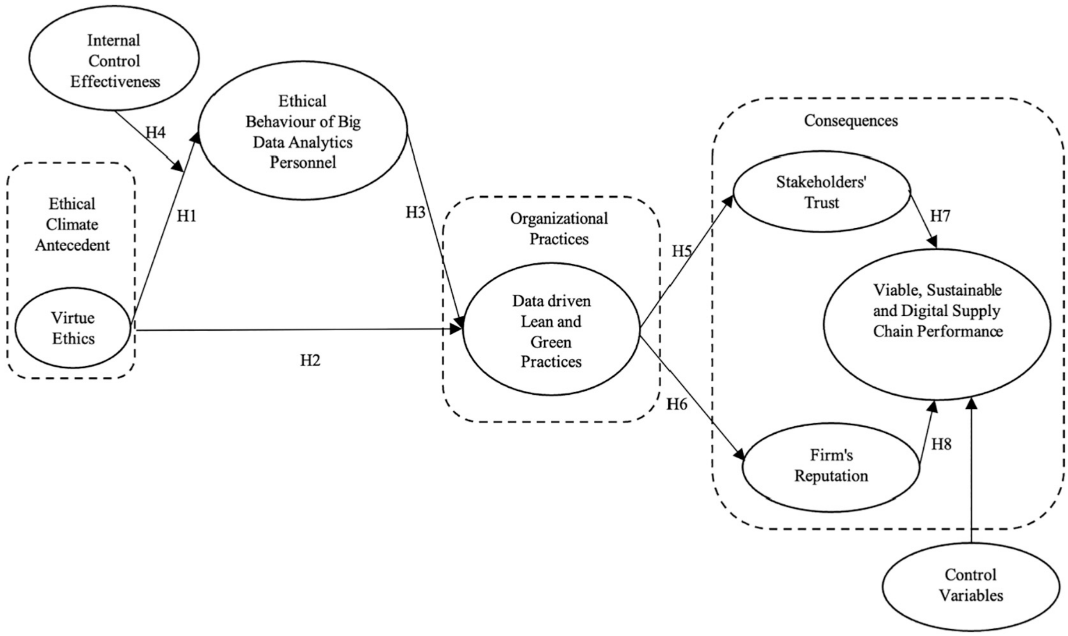

Fig. 1. Theoretical model.

sampling strategy. To ensure control and minimization of method bias in survey research we have applied common method bias and nonresponse bias tests.

4.1. Operationalization of constructs

The constructs considered in this study were measured using items from previous studies, for example, Virtue ethics (2nd order construct) was formed by empathy (9 items), Protestant work

ethic (10 items), Piety (3 items), Respect (4 items), Reliability (5 items), and Incorruptibility (3 items) was adapted from the study of Shanahan and Hyman (2003). Similarly, Internal Control Effectiveness (2nd order construct) comprised of Complexity of internal control systems (4 items), Competence (5 items), Internal Communication (4 items), and Monitoring (5 items) was adapted from the study of Hunziker (2017). Ethical Behavior of Big Data Analytics Experts (4 items) was adapted from the study of Siponen (2000), Pahnila et al. (2007), Adam and Bull (2008), Myyry et al. (2009), Alfawaz et al. (2010), and Stamatellos (2013). Data-driven Lean and Green Practices (4 items) was adapted from the study of Yu et al. (2018).

Stakeholder Trust (2nd order construct) comprised of Managerial Competence (2 items), Technical Competence (2 items), Integrity (3 items), Benevolence (3 items), Identification (3 items), and Transparency (4 items) was adapted from Pirson and Malhotra (2011).

The reputation of the firm was measured using 6 items that were adapted from Walsh and Beatty (2007). Viable, Sustainable, and Digital SC Performance was measured using 3 items that were adapted from Zekhnini et al. (2021). The details are presented in Table 1 (see annexure). The definition of the constructs has been presented in Table 2.

Table 2
Definition of constructs.

Construct's name	Definition	Source
Virtue ethics	The personal attributes of an individual that help establish their ethical nature and conduct are referred to as virtue ethics.	Gal et al. (2020)
Ethical behavior	The positive and conscious attitude of stakeholders toward the business core principles, culture, and climate in organizations.	Duh et al. (2010)
Data driven lean and green practices	Big data-driven lean and green techniques and tools aim to reduce wastages and enhance environmental performance in organizations.	Oliveira et al. (2018)
Shareholders' trust	Shareholders' faith in the organization's reliability, honesty, or capacity.	Hewitt et al. (2020)
Firm's reputation	The collective opinion of people about a firm or enterprise is referred to as corporate reputation, which results in favorable investor perceptions.	Hale and Santos (2008)
Viable, sustainable, and digital supply chain performance	By putting together, a consistent digital SC, lean, green, and sustainability paradigm description, a VSDSC model is provided.	Zekhnini et al. (2021)
Internal control effectiveness	Internal control is a procedure for ensuring that an organization's objectives in operational effectiveness and efficiency, reliable financial reporting, and compliance with laws, rules, and policies are met.	Hunziker (2017)

4.2. Sampling strategy and data collection

The samples (1200) were selected from the National Association of Software and Services Companies (NASSCOM) database using the random sampling method. The questionnaire was developed using a Likert scale on a 5-point basis. We emailed the online (Google form) questionnaire link to 1200 potential respondents working in different companies in India and members of NASSCOM. Initially, we received 172 responses and after follow-ups, we received 244 responses. We did not provide any incentives to the respondents, but the NASSCOM took interest in this survey as the senior members were properly briefed about the importance of this work with respect to practice and policy. In total, we received 416 responses which indicate the response rate is 34.66 %. We have portrayed the demographic profile in Table 3.

The profile of respondents shows that maximum responses were received from the senior age group; secondly, the highest number of respondents hold a postgraduate degree; thirdly, maximum responses were received from the senior level managers; fourthly, the highest responses were received from respondents working with companies that are operating between 10 and 20 years; and lastly, most of the respondents were from medium-sized firms.

4.3. Nonresponse bias

Nonresponse bias could be a potential concern for validating our dataset due to the use of a survey-based tool for data collection (Wamba et al., 2020; Belhadi et al., 2020, 2021b). The researchers tested data on nonresponse bias by applying a three-step process. First, bias was tested through the application of a sample fit test between paired control variables: firm size and industry ($p > 0.524$), firm size, and firm age ($p > 0.436$), industry and firm age of the firm ($p > 0.469$), all of which are within acceptable limits (Belhadi et al., 2021b). Second, the researchers compared and examined respondent data between the first wave (25 %) and the last wave (25 %) by applying analysis of variance (ANOVA) for all items of the measurement variables. The results of the statistical analysis did not show significant differences between the early and late data set ($p > 0.301$). Finally, we tested for nonresponse bias by comparing the responses of early responders (173 in this case) and late responders (243 in this case) (Lambert and Harrington, 1990). *t*-Tests were applied to the variables in this study, and the early responses were not significantly different from the late responses. Therefore, it is sufficient to infer that the study data were not affected by nonresponse bias.

4.4. Common method bias

As this study is cross-sectional, researchers have already considered the chances that common method bias (CMB) may impact the measurement constructs of the common model (Podsakoff et al., 2003; Richardson et al., 2009; Podsakoff et al., 2012). The researchers applied ex-ante and ex-post approaches to reduce the likelihood of the common method bias effect. During ex-ante steps during the research design phase, the study applied multiple procedural strategies such as collecting data for different constructs from multiple sources, unsystematic order of the variables and mixing items to minimize CMB issues. Furthermore, the researchers also assured that the study must maintain respondents' anonymity and confidentiality and were specifically told that there are no right or wrong answers, and the respondents need to choose the answer based on their own choices.

In addition, we also took a series of steps that ensure our data collection objective along with enhancing respondents' capabilities of answering accurately all the items under each construct to avoid potential sources of method bias (MacKenzie and Podsakoff, 2012). For instance, in this study, we develop the instrument in such a way that each item maintains the level of cognitive sophistication of respondents and reflects the respondent's ability and experience, of the proposed items that s/he is asked to answer. In order to manage the issue of lack of experience in thinking about the topic of study, this may affect the method bias. We make sure that the research assistants who were responsible for follow-ups do not ask the respondents for additional explanations beyond what the respondents know/show interest in (Ericsson and Simon, 1980; Nisbett and Wilson, 1977). This can be avoided by exercising caution when asking respondents about the motives for their behavior, the effects of situational factors on their behavior, or other things pertaining to cognitive processes that they are unlikely to have attended to or stored in short-term memory. The instrument was developed via literature review and suggestions from academic and non-academic experts for clear and concise language; avoiding inappropriate and complex syntax; avoiding unfamiliar terms until the endpoints to manage the item ambiguity (MacKenzie et al., 2011). In addition, the use of double-barreled items was checked to apply the items which reflect only one opinion by the respondents.

Furthermore, during the post-data collection stage, the researchers applied statistical approaches to detect and control CMB (Malhotra et al., 2006; Chang et al., 2010). In this stage, we applied Harman's single factor test operationalizing through exploratory factor analysis and confirmatory factor analysis (Podsakoff et al., 2003, 2012; Malhotra et al., 2017). The results from Harman's single factor through the EFA process yielded only 12.89 % of explained variance, which is a considerable amount lower than the threshold of 50 %. In addition, the results from CFA analysis by applying a single factor solution by using AMOS 20 revealed poor model fit (Chi-Square/df = 5.069; CFI = 0.196; RMSEA = 0.128; SRMR = 0.157). Furthermore, the Chi-Square difference test revealed no significant difference between the two models–with and without a common latent factor. These results implied that the issue of common method bias is not significant, and we can proceed with further statistical analysis.

Table 3
Demographic profile of respondents.

Demographic details	Description	Numbers	Percentage
Age group	20–30	12	2.88 %
	31–40	55	13.22 %
	41–50	164	39.42 %
	51–60	177	42.55 %
	Above 60	8	1.92 %
Educational qualifications	Postgraduate	266	63.94 %
	Graduate	128	30.77 %
	Diploma	22	5.29 %
	Class 12	0	0.00 %
	Others	0	0.00 %
Designation	Board Member	0	0.00 %
	CEO/President/Owner/ Managing Director	0	0.00 %
	CFO/Treasurer/Controller	0	0.00 %
	CIO/Technology Director	8	1.92 %
	Chief Procurement Officer	0	0.00 %
	Senior VP/VP	16	3.85 %
	Head of Business Unit or Department	19	4.57 %
	Senior Manager	212	50.96 %
	Manager	75	18.03 %
	Junior Manager	39	9.38 %
	Data Analyst	8	1.92 %
	Data Scientist	22	5.29 %
	Consultant	15	3.61 %
	Researcher	2	0.48 %
	Others	0	0.00 %
Age of the organization (years)	Above 20	23	5.53 %
	10 to 20	387	93.03 %
	<10	6	1.44 %
Firm size	Small	172	41.35 %
	Medium	233	56.01 %
	Large	11	2.64 %

4.5. Control variables

Past studies (Belhadi et al., 2021b; Wang et al., 2021; Zhou and Wang, 2021) have recommended considering firm age and firm size as control variables in the context of a firm's sustainable and digital SC performance. The statistical results justify that none of the control variables significantly influenced the firm's viable, sustainable, and digital SC performance constructs.

5. Data analysis

The details of the measurement model and structural model are presented in this section.

5.1. Measurement model

The study has established the unidimensionality by assessing the overall model fit based on fit indices. The results from the confirmatory factor analysis (CFA) reveal that the χ2 value is 307.68 with 109 degrees of freedom, which is significant ($p < 0.001$). Other fit indices are within acceptable ranges (goodness of fit-GFI = 0.90, adjusted goodness of fit-AGFI = 0.86, comparative fit index-CFI = 0.97, root mean square error of approximation-RMSEA = 0.03) (Bentler and Bonett, 1980; Bentler, 1990).

The confirmatory factor analysis (CFA) was also operationalized through AMOS-20 to assess the validity of the measure's scale (Fornell and Larcker, 1981). The results from the CFA analysis are reflected in Table 4 which provides all the values of standardized factor loadings (λ), measurement scale composite reliability (CR), and average variance extracted (AVE).

The study examined the convergent validity of the measurement model by fulfilling three standard criteria such as composite reliability (CR) should exceed 0.7; the average variance extracted (AVE) for each construct should exceed 0.5; and the construct's CR must be greater than the corresponding AVE values (Hair et al., 2006). The results from the CFA analysis explore that the values of each construct's CR > 0.70 along with AVE > 0.50; and all the CR values are higher than the AVE for each corresponding construct fulfilling the convergent validity of the measurement model.

In addition, the researchers tested discriminant validity by comparing the value of AVE of each latent construct with maximum shared variance (MSV) and average variance shared (ASV). The results from the analysis found that each construct's AVE is greater than MSV and ASV which confirms discriminant validity (Fornell and Larcker, 1981). Furthermore, the square root of the AVE of twenty latent constructs are also found to be above correlation coefficient values further suggesting that the measurement model possesses discriminant validity (Fornell and Larcker, 1981) see Table 5. Above all the values of Cronbach's alpha for all constructs is above 0.60 which also justifies the internal consistency of the data (Nunnally and Bernstein, 1994).

5.2. Structural model

After confirming the reliability and validity of the measurement model, we conducted structural equation modeling (SEM) approaches through the maximum likelihood estimation (MLE) process which is an appropriate method that allows statistical procedures for testing causal direct hypotheses (Fornell and Larcker, 1981; Jin et al., 2020; H. Wang et al., 2020). A SEM assesses the hypothesized causal relationship between virtue ethics (VE) and ethical behavior of BDA personnel (ETB) (H1), virtue ethics (VE) and data-driven lean and green practices (DDLG) (H2), ethical behavior of big data analytics personnel (ETB) and data-driven lean and green practices (DDLG) (H3), data-driven green and lean practices (DDLG) and stakeholders' trust (ST) (H5), data-driven green and lean practices (DDLG) and reputation of firms' (ROF) (H6), stakeholders' trust (ST) and viable, sustainable, and digital SC performance (VSDSC) (H7) and increased firms' reputation (ROF) and with viable, sustainable, and digital SC performance (VSDSC) (H8).

Overall, model fit statistics indicate a good fit that the $\chi 2$ value is 602.79 with 186 degrees of freedom at $p = 0.001$. Other fit statistics are also in the range to acceptable GFI = 0.952, AGFI = 0.921, NFI = 0.946, CFI = 0.947, IFI = 0.948, TLI = 0.925, RMSEA = 0.053; RMR = 0.050.

The structural model depicted in Fig. 2 reflects only significant and standardized path coefficients. The estimated model accounts for 47.9 % of the total variance in viable, sustainable, and digital SC performance in the Indian manufacturing industries setting. The results from SEM show all the direct relationship are significant and positive toward their corresponding outcome variables (see Fig. 2) (H1: VE → ETB: $\beta = 0.209$, p < 0.001, critical ratio = 2.386, H2: VE → DDLG: $\beta = 0.213$, P < 0.001, critical ratio = 2.021, H3: ETB → DDLG: $\beta = 0.249$, $P < 0.001$, critical ratio = 2.659, H5: DDLG → ST: $\beta = 0.279$, $p < 0.01$, critical ratio = 3.019, H6:DDLG → ROF: $\beta = 0.258$, $p < 0.01$, critical ratio = 2.893, H7: ST → VSDSC:$\beta = 0.331$, $p < 0.01$, critical ratio = 3.209 and H8:ROF → SDSC: $\beta = 0.279$, $p < 0.01$, critical ratio = 2.906). Thus, the study accepted all the hypotheses, interestingly stakeholders' trust is more likely to influence viable, sustainable, and digital SC performance than on the other factors. The summary of hypothesis testing is presented in Table 6.

5.3. Moderated mediation test

A moderated mediation analysis was conducted to examine hypothesis four (H4) that states internal control effectiveness moderates the relationship between virtue ethics and the ethical behavior of BDA personnel, with higher internal control effectiveness leading to higher ethical behavior of BDA personnel, by applying PROCESS macro for SPSS (Model 7 suggested by Hayes, 2018).

The statistical test of significance level in the context of direct and indirect effects toward the respective outcome variable was examined by applying 10,000 bootstrap samples to attain bias-corrected confidence intervals at a 95 % level (Hayes, 2018). The analysis embedded with mediation and moderation effect to understand the conditional indirect effect of firm's virtue of ethics on data-driven lean and green practices through ethical behavior of BDA experts as moderated by internal control effectiveness (see Fig. 3).

The study applies internal control effectiveness as a moderator of the relationship between a firm's virtue of ethics and the ethical behavior of BDA experts, which was put as a mediator of the relationship between the virtue of ethics and the firm's data-driven lean and green practices (see Fig. 3).

The moderated mediation analysis examines three analyses, firstly, the effects of the virtue of ethics on data-driven lean and green practices in the context of direct and indirect effects, through ethical behavior of BDA experts. Secondly, the effect of the virtue of ethics on the ethical behavior of BDA experts which is moderated by internal control effectiveness, and lastly the effect of the firm's ethical behavior of BDA experts on the data-driven lean and green practices.

Given the diversity of the Indian manufacturing industry, the potential relevance of firm age and firm size was considered as control variables in the moderated mediation model. The results from the PROCESS analysis revealed that internal control effectiveness positively and significantly moderated the effect on ethical behavior of big data analytics experts (effect = 0.097; $p = 0.003$) (see Table 7) and, specifically, the relationship between green self-identity and ethical behavior of BDA experts was stronger when individual manufacturing firm displayed higher internal control effectiveness(effect high = 0.687 vs. effect low = 0.497) (see Table 8), as hypothesized in H4.

Overall, the evidence from the statistical analysis also supports that the internal control effectiveness act as a partial mediator of the relationship between a firm's virtue of ethics and data-driven lean and green practices and supports internal control effectiveness as a moderator of the relationship between virtue ethics and ethical behavior of BDA experts. Hence, the results suggest that manufacturing firms who perform a higher level of virtue ethics will demonstrate a higher level of ethical behavior of BDA experts in the manufacturing firms, especially when the internal control effectiveness of the firms is high. Both ethical behavior of big data analytics experts and virtue ethics lead to higher data-driven lean and green practices. The results of the moderation-mediation test through PROCESS macro by applying model 7 are demonstrated in Fig. 3 and summarized in Tables 7 and 8.

6. Discussion

Our findings reveal that virtue ethics has a positive relationship with the ethical behavior of BDA personnel. This is a unique contribution as our work empirically validated the relationship. The concept of BDA has the potential to transform traditional manufacturing into green and lean manufacturing and the same was conceptualized using resource-based perspective theory (Belhadi et al., 2020). Gupta et al. (2020) analyzed the comprehensive view of BDA embedded in lean techniques concerning modern organizational theory. Choi and Leon (2020) assess the

Table 4
Validity test result.

Latent variables	Variable codes	Ch. alpha	Loadings (λ)	AVE	CR	MSV	ASV
Virtue Ethics (VE)	Empathy	0.897		0.503	0.9	0.31	0.281
	EMP1		0.782				
	EMP2		0.672				
	EMP3		0.624				
	EMP4		0.701				
	EMP5		0.802				
	EMP6		0.701				
	EMP7		0.712				
	EMP8		0.671				
	EMP9		0.707				
	Protestant work ethic	0.898		0.501	0.909	0.321	0.271
	PWE1		0.701				
	PWE2		0.71				
	PWE3		0.711				
	PWE4		0.732				
	PWE5		0.651				
	PWE6		0.797				
	PWE7		0.703				
	PWE8		0.692				
	PWE9		0.723				
	PWE10		0.653				
	Piety	0.879		0.753	0.901	0.374	0.276
	PIE1		0.884				
	PIE2		0.892				
	PIE3		0.826				
	Respect	0.898		0.701	0.903	0.369	0.291
	RES1		0.835				
	RES2		0.803				
	RES3		0.879				
	RES4		0.832				
	Reliability	0.896		0.654	0.904	0.29	0.261
	REL1		0.799				
	REL2		0.703				
	REL3		0.847				
	REL4		0.799				
	REL5		0.886				
	Incorruptibility	0.895		0.75	0.9	0.346	0.284
	INC1		0.823				
	INC2		0.898				
	INC3		0.876				
Internal Control Effectiveness (ICE)	Complexity of internal control systems	0.871		0.683	0.896	0.326	0.276
	COM1		0.816				
	COM2		0.824				
	COM3		0.825				
	COM4		0.841				
	Competence	0.869		0.595	0.879	0.307	0.269
	COP1		0.702				
	COP2		0.835				
	COP3		0.741				
	COP4		0.812				
	COP5		0.76				
	Internal Communication	0.837		0.579	0.846	0.358	0.286
	ICM1		0.795				
	ICM2		0.704				
	ICM3		0.801				
	ICM4		0.741				
	Monitoring	0.847		0.54	0.854	0.32	0.276
	MON1		0.814				
	MON2		0.726				
	MON3		0.706				
	MON4		0.704				
	MON5		0.721				
Ethical Behaviour of Big Data Analytics Personnel (ETB)	ETB1	0.841	0.708	0.58	0.846	0.296	0.197
	ETB2		0.768				
	ETB3		0.835				
	ETB4		0.731				
Data driven Lean and Green Practices (DDLG)	DDLG1	0.829	0.726	0.551	0.83	0.302	0.261
	DDLG2		0.714				
	DDLG3		0.804				
	DDLG4		0.724				
Stakeholders' Trust (ST)	Managerial Competence	0.861		0.685	0.867	0.3029	0.297
	MAC1		0.817				
	MAC2		0.798				
	Technical Competence	0.846		0.664	0.855	0.371	0.294

(continued on next page)

Table 4 (*continued*)

Latent variables	Variable codes	Ch. alpha	Loadings (λ)	AVE	CR	MSV	ASV
	TEC1		0.803				
	TEC2		0.772				
	Integrity	0.839		0.644	0.844	0.383	0.276
	INT1		0.751				
	INT2		0.803				
	INT3		0.851				
	Benevolence	0.859		0.677	0.862	0.319	0.293
	BEN1		0.784				
	BEN2		0.809				
	BEN3		0.874				
	Identification	0.861		0.69	0.869	0.327	0.273
	IDE1		0.794				
	IDE2		0.818				
	IDE3		0.879				
	Transparency	0.837		0.582	0.848	0.318	0.264
	TRA1		0.747				
	TRA2		0.725				
	TRA3		0.817				
	TRA4		0.762				
Reputation of the Firm (ROF)	ROF1	0.869	0.691	0.556	0.881	0.371	0.296
	ROF2		0.679				
	ROF3		0.846				
	ROF4		0.701				
	ROF5		0.721				
	ROF6		0.821				
Viable, Sustainable and Digital Supply Chain Performance (VSDSC)	VSDSC1	0.851	0.761	0.661	0.854	0.326	0.273
	VSDSC2		0.826				
	VSDSC3		0.851				

value of big data in predicting e-commerce enterprises' future actions. Big data derived from online evaluations assist businesses in obtaining accurate consumer feedback. Companies may be misled, however, by data misunderstanding or fraudulent online reviews. The researcher's ethical behavior contributes to accurate data analysis. Data-driven information management that is ethical in nature leads to a company's sustainable growth. In our study, we have empirically proven that virtue ethics has a positive relationship with data-driven lean and green practices and is another unique contribution to the literature.

Prior research had not highlighted the significance of BDA personnel in data analysis and its consequences on firm performance. The current study further explores the importance of the ethical behavior of BDA personnel in lean and green practices. The stakeholder theory is used to demonstrate that ethical behavior among big data analytics personnel is associated with data-driven lean and green practices. The evidence presented in the analysis above demonstrates that the ethical behavior of BDA personnel has a positive relationship with data-driven lean and green practices. This is also a unique contribution to the theory.

This study has focused on the importance of big data monitoring in controlling personal ethical behavior. The purpose of this study is to broaden the scope of organizational ethical theory and analyze the association between virtue ethics and ethical behavior among BDA personnel. Hunziker (2017) proposed an organizational theory-based model of internal control effectiveness. Input-output ratio, degree of target achievement, coordination efficiency, and organizational flexibility are four characteristics that are identified as having a substantial impact on overall internal control effectiveness (Hunziker, 2017). Shanahan and Hyman (2003) identified empathy, trust, respect, and trust as the core important factors of virtue ethics. The function of virtue ethics in today's data-driven company organization could be magnified by big data analytics personnel's behavior. Controlling the accessibility of big data is critical for preventing data leaks. Big data helps businesses improve their performance and make the best use of their resources (Pham and Tran, 2020). Through the analysis of the model presented in Fig. 1, this study demonstrates that the moderating influence of internal control effectiveness on the relationship between virtue ethics and ethical behavior of BDA personnel is analyzed in this study while the ethical behavior of BDA personnel played a partially mediated role. We also established the moderating effect of internal control effectiveness as a contextual element in the virtue ethics and ethical behavior of BDA experts which is a unique contribution to the literature.

According to Belhadi et al. (2020), BDA improves the efficiency and efficacy of green and lean approaches. Big data's effectiveness is determined by the professionals working with it. In the current study, the importance of ethical big data analytics behavior in the manufacturing industry is investigated. Ethical considerations should be considered in big data research analytics to protect the privacy of participants. Monitoring is necessary to safeguard data from being misused. According to the findings, the ethical behavior of BDA employees plays a mediating role in the relationship between virtue ethics and data-driven green and lean practices, thus extending the theoretical understanding.

Big data analytics speeds up information sharing among stakeholders, improving transparency. Someh et al. (2019) used stakeholder theory to evaluate the salience of each stakeholder involved in big data analytics. The stakeholder theory was used to explain why ethics is so important to stakeholders (Someh et al., 2019). The study recommends that data-driven lean approaches adhere to security, transparency, and privacy to reduce risk and establish confidence. Stakeholder trust is essential for every organization's success. Stakeholders can acquire real-time information on the business organization due to data-driven lean and green practices. This study expands on stakeholder theory by investigating the impact of data-driven lean and green practices on stakeholder trust. The manufacturing industry is rapidly adopting data-driven lean and green methods, which is strengthening stakeholder trust. Hence, data-driven green and lean practices have a positive relationship with increased stakeholders' trust levels. This is empirically proven in this study and is a unique contribution to literature.

Yu et al. (2018) demonstrated that data-driven SCM has a positive impact on the financial performance of Chinese manufacturing firms. Yu et al. (2018) measured the influence of big data analytics on organizational performance improvement using contingency theory. Big data analytics enable manufacturers to improve their lean and green processes. Data-driven lean and green practices increase the efficiency of the digital supply chain (Zekhnini et al., 2021). This study examines the influence of data-driven green and lean practices on an organization's reputation using resource view theory. The ethical supervision

Table 5
Results of discriminant validity.

	EMP	PWE	PIE	RES	REL	INC	COM	COP	ICM	MON	ETB	DDLG	MAC	TEC	INT	BEN	IDE	TRA	ROF	VSDSC
EMP	**0.709**																			
PWE	0.427	**0.707**																		
PIE	0.428	0.439	**0.87**																	
RES	0.436	0.462	0.429	**0.84**																
REL	0.416	0.477	0.479	0.398	**0.81**															
INC	0.429	0.409	0.482	0.497	0.513	**0.87**														
COM	0.431	0.407	0.471	0.426	0.519	0.419	**0.83**													
COP	0.445	0.425	0.491	0.421	0.517	0.446	0.451	**0.77**												
ICM	0.409	0.418	0.413	0.427	0.516	0.427	0.429	0.517	**0.76**											
MON	0.471	0.416	0.475	0.419	0.517	0.469	0.437	0.427	0.429	**0.73**										
ETB	0.419	0.438	0.416	0.426	0.512	0.418	0.418	0.418	0.439	0.517	**0.76**									
DDLG	0.427	0.472	0.438	0.437	0.529	0.437	0.467	0.416	0.478	0.419	0.518	**0.742**								
MAC	0.406	0.413	0.416	0.443	0.561	0.457	0.429	0.417	0.418	0.417	0.517	0.412	**0.83**							
TEC	0.432	0.426	0.409	0.447	0.513	0.454	0.473	0.425	0.439	0.429	0.516	0.416	0.479	**0.81**						
INT	0.476	0.435	0.407	0.441	0.514	0.517	0.471	0.429	0.405	0.476	0.419	0.418	0.519	0.429	**0.8**					
BEN	0.435	0.471	0.402	0.449	0.497	0.516	0.469	0.417	0.407	0.429	0.567	0.437	0.429	0.439	0.513	**0.82**				
IDE	0.472	0.429	0.403	0.445	0.479	0.517	0.436	0.439	0.406	0.437	0.529	0.471	0.437	0.417	0.526	0.426	**0.83**			
TRA	0.424	0.461	0.405	0.441	0.541	0.517	0.415	0.467	0.404	0.414	0.541	0.435	0.442	0.413	0.423	0.497	0.429	**0.76**		
ROF	0.431	0.441	0.404	0.471	0.506	0.514	0.413	0.517	0.401	0.513	0.537	0.474	0.447	0.415	0.417	0.517	0.516	0.406	**0.75**	
VSDSC	0.417	0.409	0.407	0.431	0.537	0.437	0.427	0.449	0.517	0.413	0.406	0.462	0.439	0.434	0.509	0.469	0.536	0.472	0.513	**0.813**

Notes: Empathy (EMP), Protestant work ethic (PWE), Piety (PIE), Respect (RES), Reliability (REL), Incorruptibility (INC), Complexity of internal control systems (COM), Competence (COP), Internal Communication (ICM), Monitoring (MON), Ethical Behavior of Big Data Analytics Experts (ETB), Data-driven Lean and Green Practices (DDLG), Managerial Competence (MAC), Technical Competence (TEC), Integrity (INT), Benevolence (BEN), Identification (IDE), Transparency (TRA), Reputation of the Firm (ROF), Viable, Sustainable, and Digital Supply Chain Performance (VSDSC).
Diagonal bold values represent the square root of AVE.

mechanism is bolstered by business operations driven by big data. The monitoring of big data is necessary to ensure its ethical use, which has a substantial positive impact on business enterprises' reputations. The findings of this study show that the manufacturing industry is focusing on data-driven lean and green methods to improve its reputation which corroborates with previous studies.

According to Zekhnini et al. (2021) lean, green, and digital capabilities have a considerable positive impact on the performance of the digital and sustainable supply chain. Pirson and Malhotra (2011) created a framework based on stakeholder theory, identifying six factors of stakeholder trust: honesty, technical expertise, kindness, identification, transparency, and managerial competence. This study broadens the scope of stakeholder theory and explains the significance of digital SC performance in the Indian industry. The moral requirements of obtaining, safeguarding, and suing the personal data of an individual are all covered under data ethics. Business organizations are recommended to maintain a consistent alignment between behavior and value, to mitigate risks. This builds stakeholder trust, which is essential for the digital supply chain's success. This research finding revealed that increased stakeholders' trust has a positive relationship with viable, sustainable, and digital SC performance. This is a unique contribution as well.

Corporate efficiency improves the organization's operational efficiency, which has a substantial positive impact on the firm's reputation (Kwon and Lee, 2019). Sustainable practices improve the organization's performance, elevating the firm's reputation (Kwon and Lee, 2019). As the world moves toward digitization, SC management is not exempted. The study's findings demonstrated that digital technologies are unlocking the full potential of supply chains and boosting their performance. This improves the corporate reputation. Hence, an increased firms' reputation has a positive relationship with viable, sustainable, and digital SC performance.

This paper has explored the importance of an ethical perspective on big data. While dealing with big data, ethical values lead to trust and transparency among stakeholders. According to Weston (2016), BDS is a crucial engine for the transformation of a modulated society and concluded that information flow must be controlled. This is a fundamental foundation of BDA. Liu et al. (2019) investigated the possibilities of using big data to conform to ethical standards. Apart from ethical BDA, the ethical conduct of BDA personnel is a source of concern. Firms suffer losses because of unethical usage of big data. Line et al. (2020) investigated the value of big data in the hotel and tourism industries. They also demonstrate that big data generated by digital technologies can improve trust and play a prominent role in developing relationships between businesses and their customers. This study considered a deductive approach i.e., using existing theories to build the research model and further test the hypotheses. While doing so, this study expands the scope of ethical theory of organizing and virtue ethics theory, concluding that virtue ethics play a substantial role in creating favorable and ethical behavior among BDA personnel. Previous studies have identified important ethical challenges raised by big data research in the services industry, such as honoring patient autonomy through sufficient consent, maintaining equity, and protecting participants' privacy (Howe III and Elenberg, 2020). There has been, however, a lack of similar studies examining big data-related ethical issues in the manufacturing domain. The findings of our study make unique contributions to the existing big data literature by highlighting the importance of the indirect effect of virtue ethics and ethical behavior of BDA in the improvement of viable, sustainable, and digital SC performance. Our study in particular shows that the ethical risks related to BDA must be considered in digital strategy formulation.

6.1. Theoretical implications

Cornelissen and Durand (2014) raised a very valid question: How may management researchers make fresh theoretical contributions and, as a result, potentially break new ground in management research? This

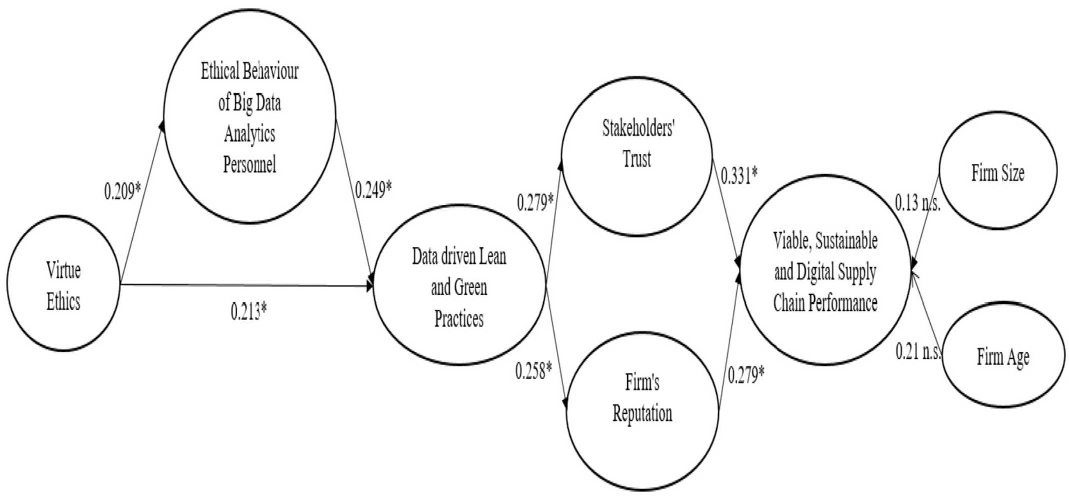

Fig. 2. Tested model.

Table 6
Hypotheses testing results.

No.	Research hypotheses	β value	*p*-Value	Decision
H1	Virtue ethics has a positive relationship with the ethical behavior of BDA personnel	0.20	<0.01	Supported
H2	Virtue ethics has a positive relationship with data-driven lean and green practices	0.21	<0.01	Supported
H3	Ethical behavior of BDA personnel has a positive relationship with data-driven lean and green practices	0.24	<0.01	Supported
H5	Data-driven green and lean practices have a positive relationship with increased stakeholders' trust	0.27	<0.01	Supported
H6	Data-driven green and lean practices have a positive relationship with increased firms' reputation	0.25	<0.01	Supported
H7	Increased stakeholders' trust has a positive relationship with viable, sustainable, and digital SC performance	0.33	<0.01	Supported
H8	Increased firms' reputation has a positive relationship with viable, sustainable, and digital SC performance	0.27	<0.01	Supported

is missing in many SCM research studies wherein researchers do not put effort to point out how their findings extend the theoretical boundary.

Developing fresh, original theoretical contributions relies on either analogical thinking and reasoning, from which new candidate inferences are produced, or contrary to fact-based thinking and reasoning, which challenges and rethinks the current theories that lead to the extension or building of new theories (Cornelissen and Durand, 2014).

Theoretical contributions are immensely important for publishing in a scientific journal. Hence, we followed the guidelines of Whetten (1989), and Reay and Whetten (2011) to showcase that we have made a strong contribution to this study. As stated in the work of Reay and Whetten (2011) theories can be improved in multiple ways. In this study, we introduced a few new constructs such as data-driven lean and green practices; viable sustainable and digital SC performance.

We tried to explain the phenomenon of interest, which is virtue ethics and ethical behavior of BDA personnel, as well as its impact on organizational practices and, finally, the outcome. Through literature review and discussion with experts from academia and industry, we

Table 7
Moderated mediation analysis.

Construct's relationship	β	P	LLCI	ULCI
Virtue ethics on Ethical behavior of big data analytics experts	0.229	0.021	0.027	0.563
Internal control effectiveness on Ethical behavior of big data analytics experts	0.103	0.017	0.019	0.497
Moderation effect of Internal control effectiveness	0.097	0.003	0.076	0.198
Ethical Behavior of BDA personnel on Data driven lean and green Practices	0.257	0.000	0.276	0.509
Virtue ethics on Data driven lean and green practices	0.207	0.000	0.309	0.619
Direct effect on Data driven lean and green practices	0.469	0.000	0.190	0.416

Notes: LLCI = lower limit confidence interval; ULCI = upper limit confidence interval.

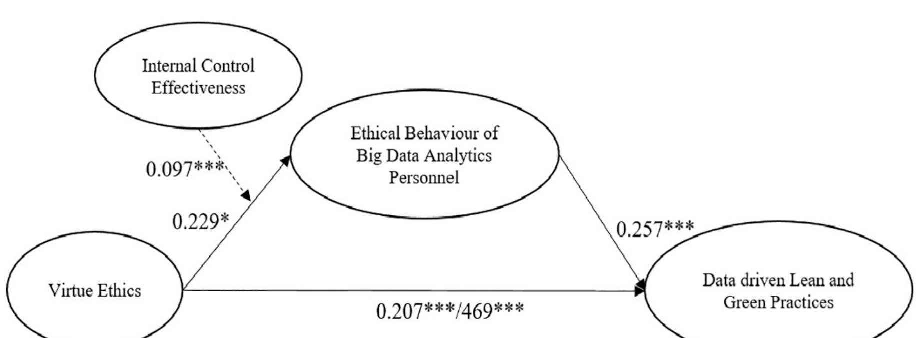

Fig. 3. The multiple moderated mediation analysis (model 7 by Hayes, 2018).
Note: Int = Interaction; $^{*}p < 0.05$; $^{***}p < 0.001$.

Table 8
Moderator analysis [conditional effect of virtue ethics on ethical behavior of big data analytics experts at values of the moderator (internal control effectiveness)].

Internal control effectiveness	Effect	Standard Error	LLCI	ULCI
Low	0.497	0.080	0.329	0.671
Medium	0.573	0.059	0.409	0.703
High	0.687	0.063	0.539	0.798

Notes: LLCI = lower limit confidence interval; ULCI = upper limit confidence interval.

have identified the major factors (virtue ethics, ethical behavior of BDA personnel, data-driven lean and green practices, shareholders' trust, firms' reputation and VSDSC performance) that are important in explaining the phenomenon of interest in this study. Further, we used three theories (Ethical Theory of Organizing, Virtue Ethics and Stakeholder theory) to link the factors and finally, we used primary data to validate the model and show that the depiction of the phenomenon is trustworthy. It is important to note that the model's predictions will hold true if the company has high internal control effectiveness and, second, has integrated sustainability into its vision and mission statement. The importance of BDA professionals in data analysis and its effects on firm performance had not been recognized in prior study. The necessity of BDA staff members acting ethically in lean and green practices is further explored in the current study.

6.2. Practical implications

The implications for practice are as follows.

The findings of our study have revealed that high/low internal control effectiveness can result in high/low ethical behavior of BDA experts. Managers must ensure that there is the availability of robust internal control effectiveness to better shape the ethical behavior of BDA experts.

Our findings also reveal that the ethical behavior of BDA experts acts as a mediator and helps firms having virtue ethics to successfully adopt data-driven lean and green practices. In this era of the fourth industrial revolution, it is therefore essential for leaders to develop a culture in the organization that is bonded with virtue ethics. Various training programs and audits related to ethics may be necessary to drive virtue ethics among employees, and in particular the experts (data engineers, data scientists, data analysts) as lack of ethics, honesty, greed, and loyalty can lead to intentional privacy breaches of others while dealing with large datasets.

The benefit of data-driven lean and green practices is that they can prevent greenwashing and reduce false claims through information sharing and greater transparency. Therefore, data-driven lean and green practices lead to an increase in stakeholders' (employees, suppliers, customers, shareholders) trust levels and an increase in corporate image significantly. Data-driven lean and green practices not only add value to the organization but add value for all stakeholders thus increasing trust levels, which will lead to a feeling of togetherness and collaborative actions that will result in the improvement of VSDSC performance.

The current study clearly indicates the necessity of developing the ethics code of practice, ethics audit, and other governance frameworks related to big data management. Second, data-driven green and lean practices must be given priority in this new-normal era to improve operational excellence. Lastly, developing viable, sustainable, and digital SC performance requires the improvement of stakeholders' trust and corporate reputation. Very little research work has shown a practical way of enhancing VSDSC performance. Therefore, in this study, the research team helps to bridge the gap between theory and practice.

7. Conclusion

This study sought to address three research questions. First, what is the relationship between virtue ethics, ethical behavior of BDA personnel, and data-driven green and lean practices; and how are they related to each other? The findings reveal that H1, H2, and H3 are supported and therefore establish the relationship between virtue ethics, ethical behavior of BDA personnel, and data-driven green and lean practices.

The study makes a unique contribution by highlighting the role of virtue ethics in driving lean and green practices in organizations, while the ethical behavior of BDA personnel plays a mediating role and is moderated by internal control effectiveness.

Second, how does internal control effectiveness play a moderating role in the relationships between virtue ethics, and ethical behavior of BDA personnel, while the ethical behavior of BDA personnel plays a mediating effect on the path of virtue ethics and data-driven green and lean practices in manufacturing industries? The findings point out that H4 is supported, and the moderating and mediating effect is also established. The findings show that moderating effect of internal control effectiveness on the path of virtue ethics and behavior of BDA personnel is positive and significant while ethical behavior of BDA experts exerts partial mediation.

Third, how can firms enhance VSDSC performance in the context of data-driven lean and green practices in manufacturing industries? The findings reveal that H5, H6, H7 and H8 are supported which establishes the relationships between the factors and reveals how VSDSC performance is improved. This study reveals that data-driven lean and green practices have a positive relationship with increased shareholders' trust and corporate image and lastly, increased shareholders' trust and corporate image both enhance VSDSC performance. Nonetheless, the most interesting observation from the study is that increased stakeholders' trust is having a stronger association with Viable, Sustainable, and Digital SC Performance. This finding takes the theoretical debate to the next level and opens many future research opportunities.

The limitations of this study include the use of cross-sectional data and sample selection from a single country. In the future, this study can be extended to other developing countries like South Africa, Brazil, and China with a focus on the services industry as well. Future research can work on the extension of the theoretical model and test it in the context of other developing countries. Other antecedents such as organizational trust culture, ethical leadership, and the structure of organizations can be used as exogenous variables to further assess the impact on the endogenous variable (VSDSC performance). The current study closes the gap in the literature by highlighting the importance of virtue ethics in big data analytics. Nonetheless, it emphasizes the importance of a continuous academic and practical discussion on ethics and big data.

CRediT authorship contribution statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A

Table 1
Operationalization of constructs.

Constructs	Sub-dimensions	Item labels	Items	Source
Virtue ethics	Empathy	EMP1	Compassion	Shanahan and Hyman (2003)
		EMP2	Caring	
		EMP3	Graciousness	
		EMP4	Attentiveness	
		EMP5	Amiability	
		EMP6	Generosity	
		EMP7	Humility	
		EMP8	Trust	
		EMP9	Contentment	
	Protestant work ethic	PWE1	Creativity	
		PWE2	Passion	
		PWE3	Competitiveness	
		PWE4	Entrepreneurship	
		PWE5	Charisma	
		PWE6	Ambition	
		PWE7	Autonomy	
		PWE8	Courage	
		PWE9	Independence	
		PWE10	Determination	
	Piety	PIE1	Saintliness	
		PIE2	Spirit	
		PIE3	Shame	
	Respect	RES1	Cool headedness	
		RES2	Tolerance	
		RES3	Cooperativeness	
		RES4	Humour	
	Reliability	REL1	Responsibility	
		REL2	Trustworthiness	
		REL3	Ability	
		REL4	Articulateness	
		REL5	Prudence	
	Incorruptibility	INC1	Honour	
		INC2	Honesty	
		INC3	Integrity	
Internal control effectiveness	Complexity of internal control systems	COM1	It is easy to determine if control activities are carried out properly	Hunziker (2017)
		COM2	Internal control activities follow a simple and comprehensible procedure	
		COM3	I can rely on well-functioning and process-embedded control activities	
		COM4	Internal control is well integrated with other management tools	
	Competence	COP1	Existing professional knowledge of the employees participating in control tasks seems very high to me	
		COP2	I fully appreciate the available competencies of the employees dealing with internal control	
		COP3	Employees are very familiar with risks and control activities in their areas of responsibility	
		COP4	No mistakes happen because of a lack of internal control competencies	
		COP5	I don't think there is a need to catch up on professional knowledge with regard to internal control	
	Internal Communication	ICM1	There is an ample opportunity for informal "hall talk" among other employees	
		ICM2	It is easy to schedule appointments with employees from different organizational units	
		ICM3	In our organization, it is easy to talk virtually with anyone you need to, regardless of rank or position	
		ICM4	There is sufficient information flow between organizational units, teams and individual employees	
	Monitoring	MON1	Procedures are in place to quickly identify control deficiencies	
		MON2	Control activities addressing risks inadequately are consistently re-evaluated	
		MON3	Revealed control deficiencies are reported to proper authorities	
		MON4	After having identified control deficiencies, corrective actions are taken	
		MON5	Through on-going monitoring activities, I can rely on the internal control systems	
Ethical behavior of big data analytics experts	N.A	ETB1	Skill in making assessments and in the application of professional knowledge, experience, understanding, common sense, or insight in regard to BDA	Siponen (2000); Pahnila et al. (2007); Adam and Bull (2008); Myyry et al. (2009); Alfawaz et al. (2010); Stamatellos (2013)
		ETB2		

(continued on next page)

Table 1 (*continued*)

Constructs	Sub-dimensions	Item labels	Items	Source
			Fixed or firmly held beliefs regarding BDA privacy and security that affect decisions regarding compliance	
		ETB3	Rightness/correctness of conduct and judgments that could affect privacy and security	
		ETB4	Willpower and control over one's personal, desires and conduct when considering actions that affect privacy and security	
Data driven lean and green practices	N.A	DDLG1	Our company builds consistent interoperable, cross-functional department databases to enable concurrent engineering, rapid experimentation and simulation, and co-creation	Yu et al. (2018)
		DDLG2	Our company aggregates customer data and make them widely available to improve service level, capture cross- and upselling opportunities, and enable design-to-value	
		DDLG3	Our company implements advanced demand forecasting and supply planning across suppliers	
		DDLG4	Our company implements lean and green manufacturing and model production virtually (such as a digital factory) to create the process transparency, develop dashboards and visualize bottlenecks	
Stakeholders' (employees, suppliers, investors, and customers) trust	Managerial Competence	MAC1	The organization can successfully adapt to changing demands	Pirson and Malhotra (2011)
		MAC2	The organization is able to reach set goals	
	Technical Competence	TEC1	The organization is very competent in its area	
		TEC2	The organization generally has high standards	
	Integrity	INT1	The organization does not try to deceive	
		INT2	The organization has high moral standards	
		INT3	The organization treats its stakeholder with respect	
	Benevolence	BEN1	The organization is caring	
		BEN2	The organization listens to my needs	
		BEN3	The organization does not abuse stakeholders	
	Identification	IDE1	I can identify with the organization	
		IDE2	My personal values match the values of the organization	
		IDE3	I feel connected with the organization	
	Transparency	TRA1	The organization explains its decisions	
		TRA2	The organization says if something goes wrong	
		TRA3	The organization is transparent	
		TRA4	The organization openly shares all relevant information	
Reputation of the firm	N.A	ROF1	The reputations of these companies are being managed well	Walsh and Beatty (2007)
		ROF2	These companies have a customer focus	
		ROF3	They keep customers informed about happenings in the company	
		ROF4	They are good corporate citizen	
		ROF5	These companies have a high reputation in the market	
		ROF6	These companies are highly reputable	
Viable, sustainable and digital supply chain performance	N.A	VSDSC1	Data driven lean and green practices help in the reduction of pollution	Zekhnini et al. (2021)
		VSDSC2	Adoption of data driven lean and green practices will ensure better economic performance with increased revenue, better market share, and reduction in compensation/penalty for ecological mishaps	
		VSDSC3	Data driven lean and green practices will not only improve operational performance but also, promote brand image and better public relations	

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