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The Impact of Big-data Analytics on Environmental Performance: The Mediating Roles of Lean Six Sigma and Green Production

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ABSTRACT

Big-data analytics has emerged as a significant tool for companies dealing with sustainability challenges due to its potential to improve the industrial sector's environmental performance. Despite this, there is no actual research on this topic to be found in the literature. The role of big-data analytics in improving Lean Six Sigma, green production, and environmental performance is investigated in this study. In addition, the role of Lean Six Sigma and green production as a mediator between big-data analytics and environmental performance is examined.

To acquire primary data, a survey method was used, with a sample of 302 replies from Jordanian industrial enterprises. Smart PLS 3.0 was used to evaluate the study hypotheses.

The study findings illustrated that big-data analytics is favorably linked with Lean Six Sigma, green production, and environmental performance. Furthermore, green production and Lean Six Sigma have positive relationships with environmental performance. Additionally, the connection between big-data analytics and environmental performance is mediated *via* Lean Six Sigma and green production. This study adds to the body of knowledge by introducing potential mediators in the link between big-data analytics and environmental performance. Jordan's manufacturing industry must establish adequate methods to address sustainability concerns and increase big-data analytics usage.

The study, which is the first to be carried out in the Jordanian setting, takes an empirical look into the relationship between big-data analytics and environmental performance in light of Lean Six Sigma and green production.

Keywords: Big-data analytics, Environmental performance, Lean six sigma, Green production.

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أثر تحليلات البيانات الضخمة على الأداء البيئي: الدور الوسيط لستة سيجما الرشيقة والإنتاج الأخضر

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ملخص

ظهرت منهجية تحليلات البيانات الضخمة كأداة مهمة للشركات التي تتعامل مع تحديات الاستدامة البيئية. تحليلات البيانات الضخمة لديها القدرة على تحسين الأداء البيئي للقطاع الصناعي. ومع ذلك، لا توجد في الأدبيات دراسات فعلية حول هذا الموضوع. لذا تهدف الدراسة إلى البحث في دور تحليلات البيانات الضخمة في تحسين ستة سيجما الرشيقة، والإنتاج الأخضر، والأداء البيئي. كما تهدف إلى التحقق من دور ستة سيجما الرشيقة والإنتاج الأخضر في توسط العلاقة بين تحليلات البيانات الضخمة والأداء البيئي.

للحصول على البيانات الأولية، تم استخدام أسلوب المسح، وتكونت العينة من (302) من الأفراد من الشركات الصناعية الأردنية. تم استخدام برنامج Smart PLS 3.0 لاختبار فرضيات الدراسة.

وأوضحت نتائج الدراسة أن تحليلات البيانات الضخمة مرتبطة بشكل إيجابي مع ستة سيجما الرشيقة، والإنتاج الأخضر، والأداء البيئي. علاوة على ذلك، تشير النتائج إلى أن الإنتاج الأخضر وستة سيجما الرشيقة لهما علاقات إيجابية مع الأداء البيئي. بالإضافة إلى ذلك، فان ستة سيجما الرشيقة والإنتاج الأخضر تتوسطان العلاقة بين تحليلات البيانات الضخمة والأداء البيئي. تشكل هذه الدراسة إضافة إلى المعرفة؛ من خلال توضيح دور الوساطة المحتمل في العلاقة بين تحليلات البيانات الضخمة والأداء البيئي. ويجب أن تستخدم الشركات الصناعية في الأردن أساليب مناسبة لمعالجة مخاوف الاستدامة البيئية والتركيز على استخدام تحليلات البيانات الضخمة.

وتعد هذه الدراسة الأولى من نوعها في الأردن التي تبحث بشكل تجريبي في العلاقة بين تحليلات البيانات الضخمة والأداء البيئي في ضوء ستة سيجما الرشيقة والإنتاج الأخضر.

الكلمات الدالة: تحليلات البيانات الضخمة، الأداء البيئي، ستة سيجما الرشيقة، الإنتاج الأخضر.

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1. INTRODUCTION

Big data has gained strategic relevance as a result of the fast development of information technology and has become one of the most valuable assets of many firms (Dubey et al., 2020; Al-Dmour et al., 2022). Big data is made up of a multitude of formats that differ in size, diversity, speed, and honesty (Tao et al., 2018). Data has led to the creation of numerous analytical tools, such as big-data analytics (BDA), to translate data into meaningful information, which can enhance decision-making and assist the performance of the company (Papadopoulos et al., 2017).

BDA and related applications are described by academics as a collection of methodologies and tools for gaining important knowledge and insights from the examination of enormous quantities of data (Wiech et al., 2022; Chen et al., 2012). Applications of BDA in manufacturing firms include quality assurance, process optimization, proactive maintenance, and product development (Yadegaridehkordi et al., 2018).

Manufacturing processes have become increasingly complicated and heterogeneous as a result of the introduction of digital information, communication, and sensor technologies, resulting in big data streaming from anywhere, at any time, and on any device (Wamba et al., 2017). Big data is undeniably important in the context of the digitalization of manufacturing (Belhadi et al., 2020). Furthermore, the huge amount of data has heightened the necessity for businesses to build BDA capabilities in order to derive useful insights from the data (Belhadi et al., 2019).

Some academics believe that encouraging industry excellence can be accomplished by implementing BDA’s two key viewpoints (Waqas et al., 2021). First, enormous amounts of big data must be acquired from the industry's surrounding environment. When compared to traditional and existing data processing systems, the outcomes of processing this type of data will reveal certain enhancements and benefits (Frank et al., 2019). Second, big data analysis is used to make changes to existing decisions and activities. As a result of combining the two views outlined above, the notion of BDA was brought to fruition (Waqas et al., 2021). Several studies have found that companies with greater BDA capabilities have better environmental performance (EP) (Belhadi et al., 2020; Kamble et al., 2020). Due to increased public attention, stricter government requirements, and long-term company profitability, there is a continual interest in incorporating EP into different parts of corporate operations (Erdil et al., 2018).

Innovative technologies like BDA can be used to make better use of resources, encourage more sustainable resource use, protect natural ecosystem biodiversity, and reduce the pressures on urban activities and infrastructure (Barnes et al., 2022). Currently, the primary motivation for using BDA in business is to enhance economic and technical conditions while improving EP (Zhang et al., 2017). From an environmental standpoint, it is critical to reduce the use of non-renewable resources and to manage them with extreme caution. At the present time, access to natural resource sustainability is a vital aspect of economic development. As a result, effective utilization of corporate resources is critical, both for businesses and for environmental preservation (Merino-Saum et al., 2018; Beier et al., 2022). In order to reduce pollutant emissions and energy consumption, BDA can also incorporate data resources into sustainability efforts (Song et al., 2018). By delivering immediate and more accurate data-rich information regarding process capabilities and by giving creative approaches to understanding and addressing problems associated with more complex processes, BDA has the potential to breathe fresh life into the Lean Six Sigma (LSS) approach (Gupta et al., 2020; Belhadi et al., 2021). BDA, in practice, provides extensive functionality assistance for data collection and analysis, design strategies, experiment construction, and making the best selections for optimal performance control (Gawankar et al., 2020).

Environmental performance (EP) is a primary concern for governments, focusing on enacting tougher regulations and laws to prevent industries from disrupting the environment. Aside from current developments in process improvement methodologies, the manner in which EP challenges are managed has also evolved (Cherrafi et al., 2016).

EP is described as the consequence of a company's strategic operations that handle (or fail to handle) its effect on the surrounding environment (Walls et al., 2012). These results cover how well the firm performs in a variety of areas, such as lowering energy use, managing gas or solid waste, as well as reducing pollution, resource wastage, and other negative environmental effects.

As a result, techniques like process optimization, Lean Six Sigma (LSS), and green production (GP) hold a lot of promise for improving EP (De Freitas et al., 2017; Kamble et al., 2020). Many industries have successfully implemented LSS as a continual improvement process (Kamble et al., 2020; Yousef & Thuneibat, 2019). According to Powell et al. (2017), LSS is an organizational enhancement process that strives to increase stakeholder value through quality improvement, efficiency, satisfaction of customers, and costs. It has been referred to as the latest era of enhancement methodologies, because it combines practices and principles from both Lean Management and Six Sigma (Snee, 2010). GP refers to the lowest level of emissions of greenhouse gases while using the least amount of energy input. In other words, improving energy or carbon efficiency is a part of green manufacturing (Yan et al., 2022; Long et al., 2016).

For greater operational performance, industrial companies are constantly improving their operations. They use LSS projects to improve their operations' performance and eliminate waste (Gupta et al., 2020; Tucci et al., 2021). Manufacturers have been motivated to improve environmental monitoring without sacrificing profits by implementing GP techniques (Choudhary et al., 2019; Qiu et al., 2020). Strong economic growth and huge production frequently wreak havoc on the environment (Zameer et al., 2020).

GP is the most crucial aspect of a company's long-term viability (Raut et al., 2021). BDA can aid in manufacturing enterprises in achieving economic gains (Papadopoulos et al., 2017), decreasing social and demand tensions (Wadmann and Hoeyer, 2018), and lowering environmental consequences (Hazen et al., 2016). Understanding the influence of big-data analytics on EP in businesses with LSS and GP would be one such inquiry. This will aid firms in determining whether developing LSS and GP technologies in manufacturing is a requirement for developing BDA capabilities to improve EP (Belhadi et al., 2020). Most businesses will use BDA to find solutions to problems like how to cut costs, shorten development times, create better services and products, or make wise judgments (Abu Afifa & Nguyen, 2022). Additionally, by incorporating environmental data into financial reporting, BDA can assist firms in promoting accountability and better satisfying the expectations of stakeholders (Saleh et al., 2022). Empirical research has indicated that the impact of big data on green practices and the environment is currently infrequent and uncertain (Benzidia et al., 2021; Song et al., 2017; Waqas et al., 2021; Nisar et al., 2021; Gupta and George, 2016; Ali et al., 2021; Beier et al., 2022). Furthermore, the impact of BDA on long-term company success is unclear and requires further examination (Gunasekaran et al., 2017).

The role of BDA in fostering the EP of the manufacturing sector has not been adequately explored in the literature review's empirical investigations (Waqas & Tan, 2022). Little research has been conducted to determine the most popular LSS tools when it comes to EP (Hammou & Oulfarsi, 2022). In this regard, Belhadi et al. (2020) and Song et al. (2018) validated and assessed the connection between BDA and sustainable firm performance and proposed that additional empirical studies should be published in order to confirm the relationship between the methodologies and theories currently in use that are connected to BDA and sustainable performance. In reality, there isn't much research that scientifically proves the link between BDA and EP.

There was also a scarcity of papers and studies on the impact of the three ideas (BDA, LSS, and GP) on EP (Singh & El-Kassar, 2019; Belhadi et al., 2020). However, there is still a research shortage on how BDA improves EP through GP and LSS. Based on the preceding, the current work aims to close the gap in this area by establishing a link between BDA, LSS, GP, and EP. Indeed, this will be achieved by examining the direct and indirect impacts of BDA on EP in the presence of LSS and GP methods as mediating variables, into which the study provides integrated insights. In particular, the study aims to accomplish the following goals:

(1) Identifying the association between BDA and LSS, GP, and EP.
(2) Shedding light on the association between LSS, GP, and EP.
(3) Investigating the role of LSS and GP in mediating the association between BDA and EP.

2. Theoretical Background and Hypothesis Development

2.1 Big-data Analytics

Big data is a complex method of storing, retrieving, and evaluating structured, unstructured, and semi-structured data in order to extract useful information and enhance decision-making capabilities (Dubey et al., 2019). Due to the massive amounts of data generated, BDA has grown rapidly and on a wide scale in recent years, presenting tremendous problems as well as unparalleled possibilities to the world. Big data, for example, can be utilized to better correctly anticipate industrial processes (Song et al., 2017).

Big data is frequently defined by the 5Vs (veracity, velocity, value, volume, and variety), making data-driven decision-making easier and allowing businesses to obtain a competitive edge (Dong & Yang, 2020; Wamba et al., 2015). Data is becoming increasingly diverse as a result of the increasing amount of data which is also being drawn from many fresh-data sources. To boost performance, more complex processes for integrating unstructured and diverse data types are required (Dubey et al., 2019).

BDA has grown in popularity as a result of its capacity to employ technology to help managers make better decisions that are data-driven rather than based on human judgment or emotion (Zhang et al., 2018). Big data has become increasingly important in the decision-making process as a result of rapid technological advancements, and it is now widely used in a variety of industries (Lioutas & Charatsari, 2020). This necessitates the creation of specialized tools for managing vast amounts of data and, as a result, spotting trends, identifying patterns, and obtaining useful outcomes (Benzidia et al., 2021).

BDA has sparked innovation by giving useful data to improve industrial processes and a way to manage environmental unpredictability, therefore increasing the organization's overall performance (Kumar et al., 2021). BDA allows for improved information decisions, which leads to a deeper understanding of the corporate processes and, as a result, higher performance management, because it allows for greater real-time decision-making (Dubey et al., 2019).

By recognizing patterns, quantifying impact, and anticipating outcomes, BDA has helped manufacturers reduce processing flaws, enhance component quality, save time and cost, enhance product life cycle management, improve labor and reduce human error, and provide manufacturers with more visibility (Kumar et al., 2021). To maximize the utilization of resources, BDA gathers important information about manufacturing operations at various phases of the production cycle. Due to its significant operational and strategic benefits, BDA is also a catalyst that may help firms boost their efficiency and effectiveness (Gupta et al., 2020; Wamba et al., 2017).

2.2 Big-data Analytics and Environmental Performance

BDA is seen as a new strategic management approach, and businesses are using big data more and more to boost employee involvement with environmental issues (Ali et al., 2021; Calza et al. 2020). Today's firms integrate the BDA concept into their processes in order to concentrate on social and environmental sustainability (Beier et al., 2020). A variety of platforms, such as machine-to-machine interactions, sensor networks, computer systems, and the Internet of Things digitalization can be used to gather data, including text, photos, multimedia, … etc. Consequently, managing this enormous amount of data that is created from numerous sources has become difficult. In order to manage this unstructured data for efficient decision-making and long-term operations, BDA may be beneficial. To attain sustainable operations, many firms struggle to include BDA in their industrial processes (Kumar et al., 2021).

Various ICT capabilities, such as BDA, are viewed as important technologies that have been incorporated into the industrial system, boosting process integration and, as a result, achieving long-term organizational success (Kamble et al., 2020). Sensors, radio-frequency identification, artificial intelligence, and analysis have proven to be most essential to improving EP (Chiarini, 2021). By enhancing capabilities, lowering uncertainty and risk, improving regular operational activities, and mass customization, BDA helps businesses stay afloat (Wu et al., 2017; Raut et al., 2020). Song et al. (2018) argued that BDA can measure EP and that past research has demonstrated that BDA capabilities help minimize waste, and enhance resource utilization and power efficiency (Belhadi et al., 2019; Dubey et al., 2019; Raut et al., 2019).

According to Zhang et al. (2017), big-data techniques can help reduce the energy use of production and maintenance activities. Mani et al. (2017) and Khattab et al. (2022) investigated how BDA can be used to reduce supply chain uncertainty and show how this might promote social, economic, and environmental sustainability. A big data-driven analytical framework for fuel manufacturing enterprises was developed by Zhang et al. (2018) with the goal of lowering energy usage and emissions.

Industrial firms can reduce waste by utilizing BDA. As a result, supply chain innovation, production, operational efficiency, and staff development, all improve, while green product creation, green innovation, and green services are also dramatically enhanced (Xu et al., 2020; Shaar et al., 2022).

BDA's function in helping global sustainable manufacturing was examined by Dubey et al. (2016). In order to improve sustainability, Kamble et al. (2018) developed an I4.0 technological framework. It also discovered some evidence of a link between BDA and EP (Kamble et al., 2020; Belhadi et al., 2020). According to the findings of the study by Waqas et al. (2021), BDA aids in obtaining a competitive advantage and EP. According to two recent studies, BDA has a good impact on social and emotional well-being (Dubey et al., 2019; Ali et al., 2021). Therefore, we propose the hypothesis following:

H1: BDA is positively associated with EP.

2.3 Big-data Analytics, Lean Six Sigma, and Environmental Performance

LSS is defined as a systematic strategy to improve results based on statistical analyses in order to reduce the occurrence of faults in the final product and remove waste in all production processes. This results in increased consumer satisfaction and a better bottom line (De Freitas et al., 2017). Since it tries to enhance operations while striving for superior results in cost, production, and quality, the LSS methodology is regarded as a viable path to enhancing organizational performance (Salah et al., 2010).

The LSS approach takes advantage of the synergy between Lean Management and Six Sigma to improve process accuracy and productivity (Madhani et al., 2022). According to Antony et al. (2016), Lean Management is not appropriate for complicated problems requiring advanced statistical methods of data analysis; however, in-depth data gathering and analysis are not required for all problems. The advantages of both lean management and Six Sigma are combined in LSS (Tissir et al., 2022). Lean Management and Six Sigma integration has decreased losses and errors while diversifying processes and contributed to business process management (Gijo et al., 2018). LSS is a data-driven method in which the efficiency of decision-making is critical at each level of the DMAIC cycle. As a result, gathering, exploring, and analyzing large volumes of data from many business units are critical (Belhadi et al., 2021).

As a result, in the present era of rising significance and availability of data, BDA has a significant potential to boost the impact of LSS in enhancing existing processes (Gupta et al., 2020). When LSS projects are integrated with BDA capabilities, decision-making processes become more efficient (Zwetsloot et al., 2018). Several studies have also found that combining BDA and LSS has several advantages. This involves boosting the speed of causation analysis between variables, improving the accuracy of outcomes, lowering LSS program expenses, and raising employee acceptance of LSS change (Gupta et al., 2020; Chiarini & Kumar, 2020; Belhadi et al., 2020).

Evidence suggests that LSS techniques help firms improve their economic, social, and EP (Cherrafi et al., 2017). Companies and individuals have utilized LSS to enhance processes and address problems (Flor Vallejo et al., 2020). Companies can profit from LSS implementation by improving their competitive advantage, response time, quality, operational expenses, and delivery timeliness, eliminating rework time, and increasing system adaptability (Gijo et al., 2018).

To achieve operational and environmental benefits, the LSS framework must be combined with sustainability tools (Ruben et al., 2018). Indeed, if corporations show real dedication and consciousness of their environmental implications, LSS may help them achieve their environmental goals (Dieste et al., 2020). Several writers describe LSS as a management system capable of delivering measurable results for organizational sustainability through an arranged structure and an ongoing approach to continuous improvement in this context (De Freitas et al., 2017).

LSS is a methodology of sustainable development that reduces negative environmental effects while also providing useful goods (Kaswan et al., 2020). According to the literature, using LSS to implement sustainability has yielded positive results in terms of both economic and EP (Chugani et al., 2017; Erdil et al., 2018). The success of implementation and operation and EP is linked, since waste is eliminated, pollution is reduced, and resource conservation is improved (Barcia et al., 2022). Several research works have demonstrated that LSS has a favorable effect on EP (Cherrafi et al., 2016; Ruben et al., 2018; De Freitas et al., 2017; Erdil et al., 2018).

According to the literature, EP has been greatly advanced by LSS efforts, such as lowering the usage of power and gases (Erdil et al., 2018). Improvements have also been recorded in natural resource and energy optimization, as well as in wastewater reduction (Cherrafi et al., 2017; Powell et al., 2017). LSS also encourages a culture shift that accelerates organizations' adoption and commitment to environmental projects, potentially lowering environmental costs (Cherrafi et al., 2016). The purpose of LSS is to minimize process mistakes, defects, and natural resource depletion in such a way that accuracy is enhanced and resource waste is reduced (Chugani et al., 2017). Furthermore, the DMAIC cycle (Define, Measure, Analyze, Improve, and Control) is appropriate for monitoring EP. As a result, businesses can deploy, manage, sustain, and enhance EP, making it more effective (Garza-Reyes, 2015). BDA skills may therefore favorably affect LSS tactics. Even if there are few examples of the creation of BDA capabilities in LSS initiatives, among those that do exist, BDA is proven to considerably enhance the effectiveness of LSS in the modern era of growing significance and data availability and the enhancement of existing operations (Rejikumar et al., 2020).

H2: BDA is positively associated with LSS.

H3: LSS is positively associated with EP.

LSS is a useful instrument for guiding top management in achieving corporate objectives to reach EP. According to the literature, implementing LSS has a positive impact on EP (Rathi et al., 2022). Furthermore, research suggests that when LSS initiatives and BDA skills are combined, decision-making processes become more efficient (Zwetsloot et al., 2018). Additionally, the combination of LSS and BDA increases organizational effectiveness by identifying and eliminating waste and defects. However, it is unable to estimate and enhance environmental factors (Rathi et al., 2022).

Evidence suggests that when LSS initiatives and BDA skills are combined, decision-making processes become more efficient (Fahmy et al., 2017). Belhadi et al. (2020) found that LSS significantly mediates the association between BDA and EP.

In fact, only a few studies have looked at the cumulative effect of BDA and LSS on EP. The findings from the literature above help us fully comprehend that companies can improve their EP by implementing a continual improvement structure that enables them to come up with fresh and novel concepts naturally with BDA and incorporate these theories structurally in LSS (Belhadi et al., 2020; Gupta et al., 2019). Therefore, we hypothesize the following:

H4: LSS mediates the association between BDA and EP.

2.4 Big-data Analytics, Green Production, and Environmental Performance

The proper deployment of GP boosts production efficiency, with a direct impact on environmental costs. It also strongly encourages a mindset of green innovation inside industrial enterprises. Additionally, GP may enhance and nurture any industrial company's green innovation capabilities (Waqas & Tan, 2022; Qiu et al., 2020). For a company to boost and maintain its green reputation and sustainable firm performance, differentiation-based GP and green innovation are crucial (Baah et al., 2021). According to Yang et al. (2022), renewable energy, sustainable economic growth, and green financing are crucial factors in the growth of manufacturing companies (Waqas & Tan, 2022).

GP focuses on reducing manufacturing's environmental effects and enhancing product utilization (Karuppiah et al., 2020). It is the first step into ecological sustainability, and it entails the use of strategic operation, ISO 14001 tools, green supply chain, environmental management, planning, as well as GP (Bhatt et al., 2020). Nowadays, many businesses make a concerted effort to examine the environmental impacts and threats to the environment (Paulraj, 2011). A company's industrial modernization strategy should include green design, source reduction, process optimization, recycling, and pollution prevention (Hariyani & Mishra, 2022; Al Shaar, 2021).

Companies have been able to be inventive in terms of product creation as well as the development of production methods, thanks to the connection between GP and environmental sustainability. These inventions have resulted in major organizational benefits, such as recruiting new consumers and carving out a market niche for them while also improving environmental, social, and financial performance (Baah et al., 2021).

Participating in GP practices helps foster positive environmental perspectives, which improves environmental standing and reputation (Baah et al., 2021). According to Gold et al. (2010), when businesses implement green strategies, like GP and green innovation, their EP improves naturally, and they are better able to adapt to regulatory measures and environmental needs. Similarly, when businesses turn policies into environmentally friendly products, they agree to obey the rules and regulations: pollution and material waste are decreased, and products are made to be recyclable. This implies that GP techniques improve EP (Gong et al., 2018; Yasir et al., 2020).

Many organizations struggle to integrate BDA into their manufacturing processes in order to gain sustainable operations (Kumar et al., 2021). Manufacturing companies, according to Dubey et al. (2016), must embrace BDA in order to stay in business. Constant monitoring and analysis of real-time operating data help in the identification and removal of bottlenecks. BDA aids in problem identification, risk reduction, performance enhancement, and downtime reduction. By minimizing resource use and implementing recycling, BDA promotes and enhances sustainability measurement in a variety of businesses (Kumar et al., 2021). The use of BDA guarantees that the GP target is met while maximizing resource efficiency (Doolun et al., 2018; Gunasekaran et al., 2017).

Kumar et al. (2021) discovered that successful BDA implementation aids in achieving the goal of long-term operations. BDA has made a substantial contribution to the growth of green products and supply chain sustainability, according to Bag et al. (2020). According to Srinivasan and Swink (2018), BDA has given organizations more influence. Researchers indicated that BDA capabilities have not played a large role in responsible manufacturing processes (by making effective decisions relating to green processes using a collection of tools, techniques, and processes) (Belhadi et al., 2019).

H5: BDA is positively associated with GP.

H6: GP is positively associated with EP.

Incorporating green practices like GP throughout all steps of manufacture, on the other hand, is a complex and time-consuming task, since it is critical to strike a balance between operational objectives, productivity, and environmental considerations in order to satisfy all parties. To improve EP, current technology must be used to incorporate GP practices throughout the entire manufacturing life cycle (Belhadi et al., 2020). Ren et al. (2019) emphasized how BDA may be used to create GP techniques. The authors developed a methodology employing BDA for boosting sustainability, quality, and reducing environmental impacts based on the examination of numerous lifecycle stages that had an impact on GP and sustainable production. This finding is supported by Singh and El-Kassar (2019), who emphasized the relevance of BDA and GP approaches in establishing sustainable skills and thus improving operations and EP. According to Zhou et al. (2020), the industrial sector's efforts for sustainability are beneficial for green innovation. According to Zameer et al. (2020), empirical data have demonstrated the mediating function of GP in the influence of business analytics and environmental orientation.

According to the findings of Nußholz et al. (2019), a sound business operation model would support resource competency measurements like GP. Furthermore, Zhang et al. (2020) discovered that GP effectively mediated the association between Chinese construction sector business models and green dynamic capabilities.

As a result, it is reasonable to assume that green practices will serve as a mechanism for the effect of BDA on EP. It is vital to investigate the mediating effects for a thorough analysis. It is possible to argue that when businesses adopt BDA, it presents to them an opportunity for green practices, which can enhance EP (Zameer et al., 2022). In light of the foregoing reasoning, it can be said that BDA will strengthen GP, which in turn will support EP. However, research on how manufacturing organizations enhance their sustainable development while being impacted by BDA is still lacking in the literature. Therefore, we propose the following hypothesis:

H7: GP meditates the association between BDA and EP.

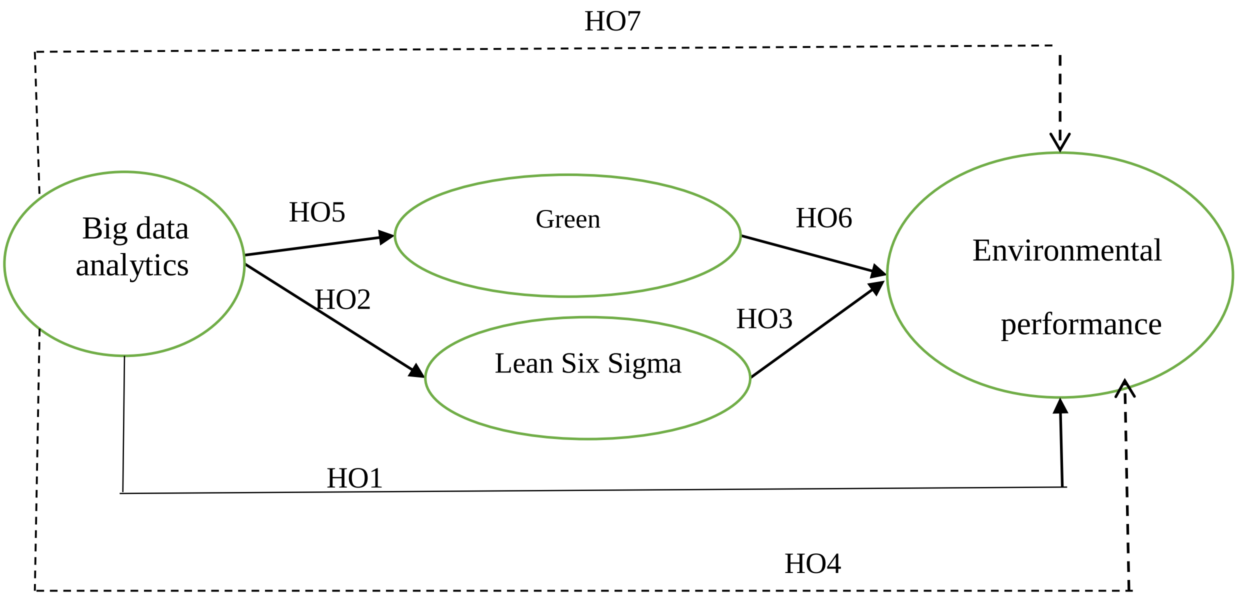

Figure (1)
Theoretical framework

3. Methodology

3.1 Measurement Development

The data collection tool for this study was a questionnaire that was sent to Jordanian manufacturing companies. The questionnaire asked for basic company information as well as measurements for each model variable. All items were adapted from previous literature and changed in the perspective of manufacturing enterprises to meet the criteria of this study. BDA was taken from (Raut et al., 2021; Dubey et al., 2020; Dubey et al., 2019) and includes an 8-item list, encompassing technical skills, infrastructure, management, employee skills, real-time data mining techniques, and data-driven-driven license.

LSS was derived from De Freitas et al. (2017), Gupta et al. (2020), Ruben et al. (2018), and Belhadi et al. (2020), and covers "waste removal, measurement metrics, DMAIC methodology, LSS tools and approaches, and variability reduction".

GP practices were adapted from Belhadi et al. (2020), Zhang et al. (2018), Raut et al. (2019), and cover green tools and techniques, energy-efficiency technologies, reconfigurable manufacturing systems, and lifecycle management.

The EP was developed by Belhadi et al. (2020), Singh and El-Kassar (2019), and Song et al. (2018), and covers five topics: wastewater, reuse and recycling, consumption of hazardous/ damaging materials, environmental cost, as well as pollution and emissions.

Table 1

Measurement model results

Items		Factor loading	CR	AVE	α
BDA			0.954	0.726	0.954
BDA1	The analytics team is knowledgeable about new tools, data management, and programming.	0.860			
BDA2	Our BDA managers are skilled in identifying appropriate uses for big data.	0.872			
BDA3	The company has excellent facilities and infrastructure.	0.861			
BDA4	Our BDA personnel are qualified.	0.849			
BDA5	Companies are now able to make better decisions because of real-time data and information analysis.	0.840			
BDA6	We regularly review our techniques and make necessary adjustments in light of the data's findings.	0.844			
BDA7	The company can handle large amounts of data by using parallel computing.	0.871			
BDA8	The use of data-driven intelligence has improved decision-making.	0.852			
GP			0.840	0.505	0.842
GP1	We have a method in place for recovering and using fresh end-of-life items.	0.648			
GP2	For environmental effectiveness, our organization redesigns production and logistic processes.	0.855			
GP3	Our company favors energy-efficient processes.	0.691			
GP4	We support the use of sustainable resources.	0.670			
GP5	Our executives make investments in energy-efficient technology.	0.688			
LSS			0.947	0.723	0.947
LSS1	Waste management is covered under our policy.	0.805			
LSS2	We have a trustworthy source of LSS metrics data.	0.851			
LSS3	Our company encourages the usage of DMAIC to solve problems.	0.847			
LSS4	Within our process, control charts (or equivalents) are well-established.	0.868			
LSS5	LSS tools assist analysts in making decisions in real time.	0.879			
LSS6	By utilizing LSS tools, we have achieved positive results.	0.816			
LSS7	We systematically detect waste within our company.	0.881			
LSS8	Our supervisors systematically keep an eye on the metrics.	0.882			

EP			0.920	0.699	0.920
EP1	Environmental cost	0.820			
EP2	Emissions and pollution	0.826			
EP3	Wastewater	0.819			
EP4	Intake of toxic or dangerous substances	0.851			
EP5	Recycling and reuse	0.860			

3.2 Sample and Data Collection

The questionnaire-based survey method was used in this study, because it captures the causal relationships among the variables in the research model and so gives generalizable assertions about the research environment. The study compiles the questionnaire from Jordanian industrial companies. The information was gathered between September and December of 2021. With the support of the Jordan Chamber of Industry, a total of 106 manufacturing enterprises throughout Jordan's various geographical regions were randomly selected. We distributed survey invitations to operational managers (analysts, technologists, executives, and managers) working in manufacturing, maintenance, IT, and environmental management units *via* e-mail. The researcher ensured that the participants were familiar with the terms BDA, LSS, GP, and EP, and that they were involved in the design and deployment of these systems and technologies in their firms. Furthermore, the majority of the respondents had been in their jobs for more than five years, implying that they had adequate knowledge to respond to the survey questions.

636 respondents from 106 industrial companies in Jordan were sent questionnaires. The invitation to participate in the survey was given to prospective respondents by e-mail, along with a cover note that clarified the topic and the study's criteria. After repeated reminders were issued to the respondents, a total of 302 completed surveys were retrieved, with a return rate of 47.48 %. The survey was conducted in two waves, with the first wave consisting of 160 questionnaires received during the first week of the study and the second wave consisting of the remaining questionnaires. According to Armstrong and Overton (1977) standards, non-response bias was investigated using a t-test for differences in means. The obtained data revealed no substantial non-response bias.

Table 2
Inter-correlation of constructs

	Variable	**Mean**	**St.d.**	**1**	**2**	**3**	**4**
1	BDA	3.714	0.870	**0.715**			
2	GP	3.771	1.013	0.654	**0.816**		
3	LSS	3.682	1.023	0.650	**0.717**	**0.795**	
4	EP	3.729	0.994	0.677	0.690	0.692	**0.791**
The diagonal (bold) numbers are the square roots of the AVE values.							

3.3 Measurement Model

Smart PLS 3.0 was utilized to test the study's hypotheses as well as the psychometric qualities of the constructs. We chose PLS path modeling over covariance-based structural equation modeling, because PLS places less demand on the underlying data distribution (Chin, 1998). Indeed, because the data did not have to be regularly distributed, the PLS approach was better for the study (Hair et al., 2019). PLS can also be a useful method for predictive modeling, hence it was appropriate for this investigation (Henseler & Sarstedt, 2013). PLS analysis was used to estimate hierarchical construct models in order to reduce model complexity (Wetzels et al., 2009).

To validate the model constructs, we used PLS modeling. We evaluated indicator reliability, construct reliability, convergent validity, and discriminant validity to assess the model.

First, the indicators' reliability was assessed using the criterion of loadings greater than 0.70 (Hair et al., 2019). This criterion was met, as stated in Table 1. Second, Cronbach's alpha and composite reliability were calculated to determine construct reliability. While Cronbach's alpha is supposed to be greater than 0.7, composite reliability should be greater than 0.6 (Sarstedt et al., 2017). A further examination of Table 1 reveals that Cronbach's alpha and composite reliability scores both exceeded their respective minimal limits of 0.7 and 0.6. As a result, the reflective model can be said to be free of worries about dependability and convergent validity.

Third, the average variance extracted (AVE) was examined for convergent validity, with a threshold value of 0.5 (Hair et al., 2019). Table 1 shows that AVE values of the variables are greater than 0.5, indicating that they meet this condition. Finally, the constructs' discriminant validity was evaluated (Fornell & Lacker, 1981). Table 2 shows that the AVE square root values are larger than the intra-construct correlations, indicating that discriminant validity is sufficient.

Table 3
Direct effect

Direct effect	**t- value**	**Path coefficient**
BDA → EP	24.497	0.779***
BDA → LSS	17.706	0.749***
LSS → EP	2.863	0.293**
GP → EP	3.316	0.330**
BDA → GP	22.464	0.781***
Explained variance proportion R^2 of GP	0.613	
Explained variance proportion R^2 of LSS	0.563	
Explained variance proportion R^2 of EP	0.735	

4. Structural Model and Mediation Analysis

To evaluate the model and see whether our hypotheses were supported, we used Smart PLS. The investigation was split into two parts. The direct hypotheses (Hypotheses 1-3, 5 and 6) were tested first, followed by the indirect hypotheses to the test (H 4 and H 7).

Table 3 lists all of the structural model's direct path coefficients and p-values. The path from BDA to EP (β= 0.779, p<0.001), LSS (β= 0.749, p<0.001), and GP (β= 0.781, p<0.001) are all statistically significant, indicating that H1, H2, and H5 are all supported. H3 is supported, since the path from LSS to EP (β= 0.293, p<0.01) is noteworthy. The path from GP to EP (β= 0.330, p<0.01) is significant, implying that H6 is confirmed.

We investigated the Smart PLS outputs on total indirect and particular indirect effects using bootstrapping approaches with 300 replications for the two mediation hypotheses (Nitzl et al., 2016). Since the probability value of the overall indirect impact is significant, our results suggest that mediation exists in our model. The impacts of the individual mediation variables are not taken into consideration in this conclusion for the total indirect effect. It is vital to evaluate the specific indirect impacts when analyzing them separately.

As shown in Table 4, the findings of the specific mediational effects corroborate the occurrence of the two mediation effects, with p-values that are statistically significant in both cases. As the direct effect of BDA on EP is not considerable, our model can be described by a full mediation effect. As a result, H4 and H7 were supported. We initially examined the entire model using the R-square and the P-value of every path coefficient in order to assess the structural model (Sarstedt et al., 2017). The path coefficient estimates for each path were significant, with R^2 values ranging from 0.563 to 0.735. The coefficients of correlation, a global fit measure for PLS path modeling that is limited between 0 and 1, were used to evaluate the entire model (Nitzl et al., 2016). 0.836 was the GoF. For a model with large effect sizes, the GoF cut-off value should be 0.360 (Wetzels et al., 2009). We determined that our model matches well, because our value surpassed this recommendation.

Table 4
Indirect effects

Type of effect	**Mediating effect**	**t- value**
Total indirect effect	BDA → EP	7.209***
Specific mediational effect	BDA → LSS → EP	3.335**
Specific mediational effect	BDA → GP → EP	4.634***
Note: *p < 0.05; **p < 0.01 ***p < 0.001.		

5. Discussion

5.1 Discussion of the Results

It is a good idea to concentrate on BDA, GP, and LSS in order to address the numerous environmental concerns facing the industrial sector. Jordan is now dealing with a number of environmental issues, including environmental pollution largely caused by the industrial sector. To address environmental issues, the Jordanian Ministry of Environment has implemented strong environmental legislations and guidelines. Numerous environmental regulations and laws, as well as pressure from outside stakeholders, may encourage the Jordanian industrial sector to concentrate on GP and LSS in order to improve EP. Therefore, Jordanian manufacturing companies should alter their manufacturing processes by concentrating on BDA, GP, and LSS. Consequently, the goal of this research was to raise EP.

We are concentrating on the Jordanian industrial sector in our study. The research works previously described used data from industrialized economies and operating systems, which are distinct from the economy and operating systems of Jordan. Consequently, it is necessary to develop approaches to implement BDA, LSS, and GP in the Jordanian industrial sector in order to improve EP. The findings showed that BDA is associated with EP, which is consistent with previous research (Waqas et al., 2021; Dubey et al., 2019; Ali et al., 2021; Kamble et al., 2020; Zhang et al., 2018; Belhadi et al., 2020; Kamble et al., 2018). BDA offers a comprehensive and rapid solution for analyzing large amounts of environmental data generated across the organization, as well as assistance in navigating the complexities of environmental challenges. By analyzing data acquired from numerous sources, real-time information received from diverse value chain partners assists firms in efficiently allocating their production resources, such as materials, power, water, and products. Enhanced transport and logistics planning, as well as the use of advanced monitoring and tracking systems, serve to minimize energy usage, reduce waste, monitor raw material inventory levels, and maximize consumption efficiency.

The findings of the study showed that BDA is associated with LSS, which is aligned with previous research (Gupta et al., 2020; Zwetsloot et al., 2018). If the data is adequately examined, additional information leads to improved and more reliable conclusions regarding a certain state. As a result, big data holds a lot of promise. To acquire more reliable and better findings, data mining and BDA approaches are required. BDA is a supplement to LSS that tries to get deeper insights into operations. BDA helps discover and track genuine transactions by pulling information from event logs, which can help eliminate process variances and waste, because LSS is process-focused. BDA also aids in reducing the time it takes to acquire data from various sources, as well as delving further into root cause analysis and identifying accurate and efficient business cycles.

The findings revealed that BDA is associated with GP, which is consistent with previous research (Kumar et al., 2021; Bag et al., 2020; Gunasekaran et al., 2017; Belhadi et al., 2019). They discovered that BDA had a detrimental impact on green lean techniques and quality assurance, which is contrary to earlier studies (Raut et al., 2019). Administrators can properly plan and perform GP development operations thanks to BDA's capacity. BDA provides excellent potential for the development of environmentally friendly goods and services that meet the needs of worldwide customers. Predictive analytics could be applied to forecast how well a green product will perform in the field. Accurate forecasting will help determine the best marketing and operations tactics, and provide you with better control over your production costs. Organizations that use BDA technologies can take a proactive strategy and be one step ahead of their competition in the market. New GP aids in the elimination of new green product failures.

The findings showed that LSS is associated with EP, which is consistent with prior research (Cherrafi et al., 2016; Ruben et al., 2018; De Freitas et al., 2017; Erdil et al., 2018). However, this runs contrary to other studies, such as Belhadi et al. (2020), who found a negligible impact of LSS on EP, as well as Venkat and Wakeland (2001), who argued that lean management is not always environmentally friendly. GP has an impact on EP, and this is supported previous research (Kumar & Chakraborty, 2022; Gong et al., 2018; Yasir et al., 2020). By minimizing greenhouse gas emissions in a company's logistic operations, LSS and GP can improve EP. Maintaining inventory levels in businesses can considerably cut carbon emissions and reduce waste generation. Inventories, wastage, and carbon emissions will all be reduced.

The findings revealed that LSS mediates the association between BDA and EP, which is consistent with previous research by Belhadi et al. (2020), and Inman and Green (2018), but contradicts the findings of Raut et al. (2019), Ruben et al. (2018), and Erdil et al. (2018). Strong BDA capabilities will strengthen the LSS's capacity to meet the long-term improvement objectives required to drive environmental projects, as EP is dependent on sustainability with a focus on continual improvement (Gupta et al., 2019). Environmental measurements must be integrated into LSS programs to ensure that gains in EP occur as a result of Lean Management and Six Sigma production techniques. In the lack of BDA skills, however, complicated environmental measures become unmanageable. Overall, the findings of our study imply that BDA can stimulate LSS methods, resulting in increased EP.

GP is found to mediate the association between BDA and EP. This result is in line with the findings of Belhadi et al. (2020). BDA integration enables environmental performance evaluation and the development of algorithms to improve the life cycle at various phases, allowing for the establishment of a life cycle monitoring system for products and processes. Using BDA, the integration of LSS and GP can be improved even more. In reality, both LSS and GP are well-known for requiring a large amount of data in order to enhance productivity and meet their implementation objectives. Both LSS and GP are data-driven, and they will enhance BDA's ability to give rich data that would be unavailable in a traditional company without BDA capabilities.

5.2 Managerial Implications

As a result of the implementation of BDA, businesses have gained a more effective means of handling large data. The term "BDA" refers to a new way of thinking about how to handle and control big data in an advanced and efficient manner, as well as new hardware, software, and operational systems and procedures. Our experimental results show the importance of BDA as a regulatory capacity to raise EP both directly and indirectly through the combination of LSS and GP as mediating variables. Managers grappling with when and how to apply BDA to improve EP will notice that our findings are particularly useful. This study provides evidence that academics and professionals have a thorough understanding of the direct and indirect effects of BDA on EP by examining the process of industrialization in Jordan.

The current study also paves the way for additional exploratory research into how BDA might work in tandem with development initiatives to support manufacturing enterprises in achieving enhanced environmental performance in diverse circumstances. Organizations can focus their top management effectiveness on overseeing the BDA activities within the big data environment and encouraging BDA decision-making capabilities to successfully enable the necessary actions.

Collaboration and sharing of knowledge, however, are unavoidable elements. Therefore, significant engagement between data providers and decision-makers should be established by enterprises' leadership to improve BDA integration, green production infrastructure, and sustainable company performance.

The findings revealed that BDA has a direct impact on LSS, GP, and EP. This means that enhancing BDA skills can deliver maximum value to businesses while also demonstrating to decision-makers the long-term value of BDA investment.

Practitioners can use the findings to gain a thorough understanding of the LSS strategy. The study makes it easier for future researchers to apply LSS techniques in a systematic manner at various stages of the LSS.

Through a comprehensive understanding of the essential components of this sustainable strategy, the current study will assist manufacturing managers in integrating the LSS approach into their business process. This study further encourages practitioners to use LSS in the sector by methodically using the suggested framework for enhanced EP.

According to the research, BDA and EP should be improved. By focusing their top management effectiveness on managing the BDA operations in the big data context and improving BDA decision-making abilities to successfully support the necessary measures, Jordanian manufacturing companies should improve their BDA. Collaboration and sharing of knowledge, however, are unavoidable elements. In order to improve BDA integration, GP, LSS, and EP, the leaders of organizations should build a collaborative partnership between data suppliers and decision-makers. The senior management should take an active part in promoting GP, LSS, and EP in the context of the Jordanian manufacturing industry by setting clear goals, communicating them to all managerial levels, and supporting the adoption of BDA. Additionally, industrial companies ought to invest in BDA systems, and top management ought to set an example by implementing BDA in GP and LSS. In order to maximize the effectiveness of BDA, manufacturing companies should also manage big data using a variety of cutting-edge technologies.

5.3 Limitations and Future Research

The study has the following limitations.

To begin, the study gathered data at a single point in time. Expanded research will add to our knowledge by revealing causal links between external and endogenous structures. Furthermore, using longitudinal data may lessen the frequent bias strategy of using information from one source at a time to weaken study results.

Second, the results of a very small sample size from the manufacturing industry in a developing economy (Jordan) may have affected this conclusion, and it's unclear whether these findings can be applied to other organizations. To address this limitation, future studies could rely on a broader spectrum of other fields. Furthermore, the results will be validated in other poor nations.

Third, future research might look at the moderating or mediating role of other variables, like green innovation, knowledge sharing, and green LSS, which could alter the impact of BDA on a company's EP. Future research could include an investigation into the usage of BDA in social performance.

5.4 Conclusion

Companies are very interested in EP, since it shows how effectively they have handled environmental issues in the past. Practitioners and researchers are actively working to combine EP with contemporary methods and tools like LSS and GP. However, this investigation's empirical results have supported the notion that BDA has a direct effect on EP. Our mediation findings supported the function of LSS and GP in mediating the relationship between BDA and EP. As a result, the overall findings of this study suggest that Jordanian manufacturing companies provide BDA, LSS, and GP with a higher amount of weight in order to improve EP.

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