

Unraveling the transformation: the three-wave time-lagged study on big data analytics, green innovation and their impact on economic and environmental performance in manufacturing SMEs

Harnessing big
data analytics in
manufacturing
SME

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Abstract

Purpose – The firms' adoption and improvement of big data analytics capabilities to improve economic and environmental performance have recently increased. This makes it important to discover the underlying mechanism influencing the association between big data analytics (BDA) and economic and environmental performance, which is missing in the existing literature. The present study discovers the indirect effect of green innovation (GI) and the moderating role of corporate green image (CgI) on the impact of BDA capabilities, including big data management capability (MC) and big data talent capability (TC), on economic and environmental performance.

Design/methodology/approach – A time-lagged design was employed to collect data from 417 manufacturing firms, and study hypotheses were evaluated using Mplus.

Findings – The empirical outcomes indicate that both BDA capabilities of firms significantly influence green innovation (GI), which significantly mediates the relationship between BDA and economic and environmental performance. Our findings also revealed that CgI strengthened the effect of GI on economic and environmental performance. The empirical evidence provides important theoretical and practical repercussions for manufacturing SMEs and policymakers.



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Originality/value – This study contributes to the literature on BDA by empirically exploring the effects of MC and TC on improving the EcP and EnP of manufacturing firms. It does so through the indirect impact of GIs and the moderating effect of CgI, thereby extending the Dynamic capabilities view (DCV) paradigm.

Keywords Big data analytics, Economic performance, Environmental performance, Corporate green image, Green innovation, Dynamic capabilities view, Manufacturing SMEs

Paper type Research paper

1. Introduction

The utilization of contemporary technologies by corporations has led to an abundance of data, raising challenges related to sustainability and capabilities (Aydiner *et al.*, 2019). The strategies employed by these firms in extracting valuable insights from this extensive data are pivotal in establishing their competitive edge and innovation capabilities (Su *et al.*, 2022). Scholars and practitioners advocate for the adoption of big data analytics (BDA) as a means to enhance the dynamic capabilities of firms, thereby bolstering their operational sustainability at the business process level (Nizetić *et al.*, 2019; Mehmood *et al.*, 2023f). This enhancement in dynamic capabilities is crucial for businesses to develop a competitive advantage, necessary for addressing environmental concerns and meeting sustainability criteria. Implementing BDA in industries not only augments their competitive advantage but also facilitates precise and timely decision-making, essential for the industries' sustainable economic growth. Moreover, the application of BDA methods can significantly refine innovation processes and overall industry performance (Capurro *et al.*, 2021).

Investment by firms in BDA techniques has been continuously rising worldwide due to their desire to gain maximum profit and attain sustainability of competitive advantage (Akter *et al.*, 2016). The technique has given vast attention by experts and scholars in recently because of its capability to revolutionize the whole process of business and theory management and is considered a hot issue in the current business environment (Mishra *et al.*, 2018). General Electric and Accenture's research has shown that about 89% of firms think applying big data techniques is important to remain competitive and increase their market share (Columbus, 2014). The firms consider BDA a critical technique for obtaining crucial information and insights from big data that cannot be obtained using simple analytical techniques (Mishra *et al.*, 2018). The firms apply the information obtained using big data to compete in the rapidly volatile business environment (Sestino *et al.*, 2023). Though the technique of BDA has been applied in different fields of industries, Google and Amazon are pioneers in adopting the big data and have performed well based on their capability compared to their competitors exploiting the data (Barton and Court, 2012). The USA-based BSA Software Alliance has found that 56% of companies who have applied the BDA in their business process display an increase of more than 10% in their growth (Columbus, 2014). Moreover, BDA can support firms to attain an advantage through the sustainable development of products and sustainable innovation.

Usually, the technique of BDA comprises variety, volume, veracity, value and velocity, termed as the five V's and helps to increase the environmental performance, encourage practical notions, realize the goals of sustainable development and acquire competitive benefits in the present dynamic markets (Tao *et al.*, 2018). Manufacturing firms can improve their operation by using two notions of the BDA, which include, firstly, the extensive data collection from the external and internal environment of the firms and, secondly, the application of big data in business analytics to suggest the modifications required the decisions to improve the operations. Business analytics comprises the capabilities, including the management capability (MC) and the talent capability (TC), through which the organizations evaluate their strategic move and plan their businesses successfully. The inclusion of BDA in green innovation (GI), which is classified into green managerial innovation (GmI), green process innovation (GPcI) and green product innovation (GPrI) (Chen, 2008), may give the business organizations a green

image. A corporate green image (CgI) plays a significant role in changing the attitude of industries toward the management and protection of the environment and motivates them to modify their management attitude and business models, which influences GI (Chen, 2011). The firms with a strong sense of CgI, when forced to address the environmental concerns, stimulate the firms' capabilities which culminates in GI (Chen and Chang, 2013). The strategies adopted by the industries on GI provide the opportunity to make their economic and environmental performances sustainable (Chen, 2011).

Moreover, the inclusion of GI in the production process is crucial for improving the organizations' environmental parameters and achieving sustainable development goals (SDGs). GI denotes the innovations that encourage development of the green process, green products and green management that lead to sustainably acquiring competitive advantage and efficiently and effectively protecting natural resources (Waqas *et al.*, 2021). The firms can distinguish their products, enhance the quality of products and decrease the production cost using product, managerial and process innovations (Kim and Srivastava, 1998). In the present competitive age, business firms may attain the equilibrium between environmental responsibility and profitability by coordinating the environment, society and economy (Waqas *et al.*, 2021). Therefore, manufacturing SMEs that stress the statutory necessities and want to avoid environmental deterioration could not increase their profit by following the environmental standards in the innovation of their product, processes and/or management.

Furthermore, as natural resources and environmental issues have become more complicated, investment in GI has become a profitable policy for manufacturing SMEs to improve economic and environmental performances. The promotion and cultivation of GI in the production of novel products and services play a crucial role, particularly when the demand by customers for services and products with greener features is rising (Zameer *et al.*, 2020). Hence, globally the investment by the firms in BDA and related technologies such as MC and TC is rising to improve their performance and to develop measures to solve environmental issues by reducing the production of industrial waste and minimizing the dependence on natural resources. The studies are required to identify the factors affecting the performance of the manufacturing industries in the Indian context. Most of the earlier studies on BDA and the performance of the firms have analyzed and verified the relations between various predetermined factors and ignored the impact of BDA (MC and TC) on environmental and economic performance and the indirect influence of GPrI, GPcI and GmI and the moderating role of CgI on EcP and EnP.

This study investigates the effect of BDA (MC and TC) in enhancing the EcP and EnP of manufacturing SMEs in the Indian context. Despite the unprecedented growth of the economy and the remarkable development of infrastructure, the application of BDA is still low in the Indian manufacturing industries (Shi *et al.*, 2019). Besides, the Indian manufacturing industries have numerous other problems, including poor innovation capabilities, absence of application of GI practices, lack of renowned global brands, mass production with poor quality, high dependence on essential technologies, consumption of a large amount of energy, poor management of resources, generation of a large amount of waste, sever issues of environmental pollution and poor digital infrastructure (Waqas *et al.*, 2021). These problems have a negative impact on sustainability and sustainable development of the Indian manufacturing SMEs. Our proposed conceptual framework can guide other developing countries and significantly contribute to the manufacturing SMEs of Asian countries. Hence, it is required to develop practical methods for improving the global reputation of the Asian manufacturing industries to encourage the world's manufacturing industries to work with them.

This study gains significance in the context of manufacturing SMEs, which not only exert a substantial environmental impact but also hold a pivotal social role due to their extensive employment base. It seeks to explore the following research questions: (1) How do BDA,

specifically MC and TC, influence GPrI, GPcI and GmI? (2) Do GPrI, GPcI and GmI mediate the relationship between BDA (MC and TC) and the economic and environmental performance of these SMEs? (3) Does CgI in manufacturing SMEs moderate the relationship between GI (GPrI, GPcI and GmI) and EcP, EnP? The advent of advanced technologies poses new challenges to industry. Firms in this sector are evolving their dynamic capabilities to enhance operational sustainability at the business process level. Employing BDA can optimize business processes, thereby conserving resources, reducing lead times, increasing customer satisfaction and bolstering sustainability (Yadav *et al.*, 2017). In the era of the fourth industrial revolution, BDA can be leveraged for plant automation (Tseng *et al.*, 2018). This research aims to investigate workforce capabilities, including talent and managerial capabilities, which support the implementation of BDA (MC and TC) to enhance operational performance and sustainability (refer to Figure 1). However, existing literature inadequately addresses the impact of BDA on the development of GPrI, GPcI and GmI and their subsequent effects on the EcP and EnP of manufacturing SMEs. Therefore, this research primarily aims to examine the role of BDA in improving the EcP and EnP of manufacturing SMEs.

2. Literature review

2.1 Big data analytics (BDA) capabilities and green innovation (GI)

According to Wamba *et al.* (2017), BDA is the technique applied to handle and obtain information from large data, improving decision-making and production activity. The mechanism of BDA includes the handling and obtaining of valuable information from the data having volume, variety and velocity which cannot be performed using traditional data analysis techniques (Lozada *et al.*, 2019). The profitability and productivity of data-driven firms are more than their competitors. BDA offers insight into the present and future conditions of the firms and the requirements to improve their products and services (Lavallo *et al.*, 2011). Hence, BDA comprises numerous datasets, including analytical methods, tools and solutions employed to effectively and efficiently assess and maintain complicated data sets. BDA plays a vital role in mitigating disasters and properly empowers business firms to

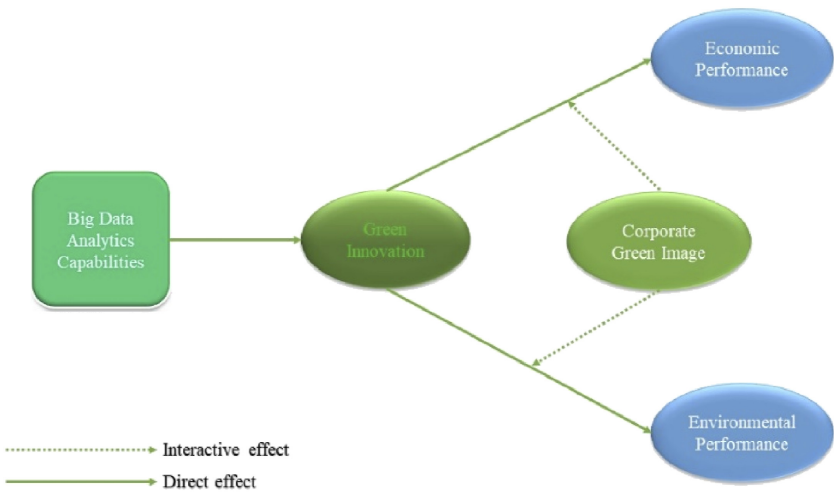
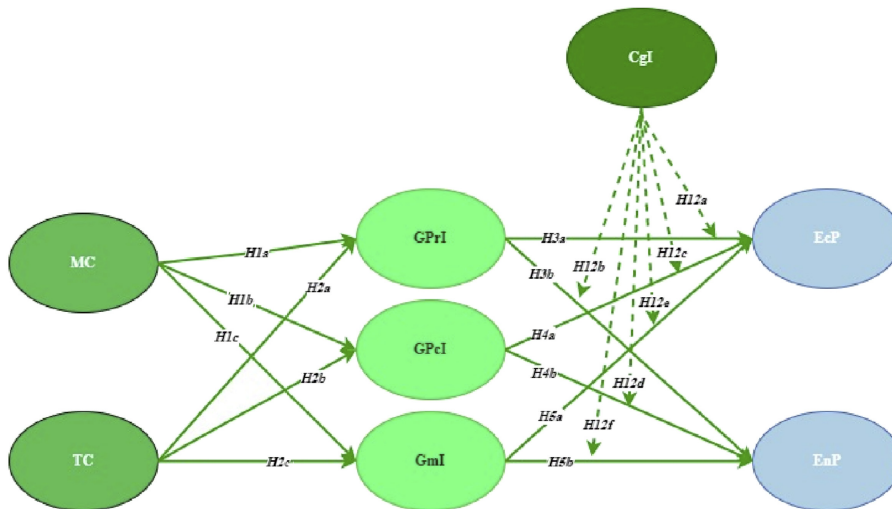


Figure 1.
Conceptual model

respond to disruptive situations (Redman, 2014). BDA has been successfully applied by different types of industries, including the auto industry, manufacturing firms, mining industry and supply chain management to improve their services and products as per the market demand. The technique helps the business firms to gain a competitive advantage and improve their economic performance and environmental performance as BDA significantly improves their information process and helps them to effectively handle the production and supply operations as per the customer demand (Waqas *et al.*, 2021). BDA has helped the construction industries improve their environmental performance and resource conservation by minimizing waste generation. The business firms with the BDA capability have positively improved their performance of the employee, supply chain innovation, production and operational efficiency and significantly increased their ability to develop the green product, green services and GI. Lozada *et al.* (2019) have found a positive association between BDA capabilities and co-innovation, as these capabilities help industries procure green resources. The BDA capability is the business firms' capability to give an insight into the new opportunities to improve the capabilities of innovation and competitive advantage by employing supportive infrastructure, talent and management capabilities (Mikalef *et al.*, 2019). BDA capabilities of business firms comprise management capabilities and technology capabilities (Akter *et al.*, 2016). However, this research identifies the effect of BDA management capabilities (MC) and technology capabilities (TC) on economic and environmental performance through GI (GmI, GPcI and GPrI) (see Figure 2).

The MC of a firm determines its overall performance and the adoption of GI (Chiou *et al.*, 2011), which increases the EcP and EnP of the firms. In this research, GI refers to GmI, GPcI and GPrI. MC is the ability of a business firm to manage its BDA resources as per the firm's preferences and requirements. MC empowers managers to make effective strategies to



Note(s): Dotted lines show interactive effects while solid lines shows direct effects; H6a&b indirect effect of GPrI between MC and EcP & EnP; H7a&b indirect effect of GPrI between TC and EcP & EnP; H8a&b indirect effect of GPcI between MC and EcP & EnP; H9a&b indirect effect of GPcI between TC and EcP & EnP; H10a&b indirect effect of GmI between MC and EcP & EnP, H11a&b indirect effect of GmI between TC and EcP & EnP

Source(s): Authors' own creation

Figure 2.
Hypothesized relationships among studied variables

produce innovative green products as per the demand of customers to minimize the chances of product failure (Zhan *et al.*, 2018). Bag *et al.* (2020) have identified a positive relation between GI and MC and have suggested that business firms can promote GI through the proper development of management capabilities. Therefore, SMEs can improve performance and sustainability by applying BDA management capabilities (MC) that substantially impacts GI. Therefore, this study postulates the following hypotheses.

H1. MC has a direct positive impact on (a) GPrI, (b) GPcI and (c) GmI.

The technological advancement and availability of a large amount of data have forced business organizations to formulate policies for the improvement of the capability of employee talent (Shah *et al.*, 2017). TC allows a business organization to enhance the ability of its employees through the investment of capital and time in the development of skills, including management, analysis and maintenance of data, programming and management of projects (Akter *et al.*, 2016). Malik and Singh (2014) found an effective impact of TC on the development of employees of business organizations and improves their leadership quality. Leaders emphasize the development of innovative products and services, giving business firms a competitive advantage (Marshall *et al.*, 2015). Applying BDA systems improves employees' competencies to produce learning and innovative environment in business firms and helps provide green innovative services and products (Chen *et al.*, 2006). Hence, the TC significantly influences the employee's performance and competencies, which helps in development of innovative green products that give the business firms a green image and competitive advantage leading to improved economic performance and environmental performance. The findings from the literature discussed above have formed the base to formulate the following hypotheses in the present research.

H2. TC has a direct positive impact on (a) GPrI, (b) GPcI and (c) GmI.

2.2 Green innovation (GI) and economic performance

The innovations help the business firms to deliver the products and services as per customer demand and to attain competitive advantage, which has a considerable impact on the reputation of the business firms and helps them to improve their environmental and economic performances. Innovation is termed as GI when it helps business firms to improve their economic performance by improving energy efficiency, waste recycling, pollution control, product design, processes and managerial skills (Chen *et al.*, 2006). GI identifies and uses the available resources to manufacture products of high value at a minimum cost, which is required to achieve a competitive advantage (Gürlek and Tuna, 2018). GI supports the provision of cleaner products and services, improves the firms' production efficiency and helps to improve economic performance in the uncertain market environment (Asadi *et al.*, 2020). Several studies have indicated that the GI adopted by numerous manufacturing industries across the globe has improved their competitiveness in the market (Sellitto and Hermann, 2019). Ge *et al.* (2018) identified that firms could achieve a sustainable economic performance by adopting GI. Dang and Wang (2022) found a significant impact of GI on the environmental performance of hospitality companies. Thus, GI and economic performance and environmental performance have a significant relationship; the proper application of GI in manufacturing can be improved. According to Chiou *et al.* (2011), GPrI is defined as the improvement in the design of a product to decrease its negative environmental effect during the product life cycle. GPrI provides business firms with new opportunities and helps them improve their economic performance. This helps the firms to produce and deliver the products using lesser toxic substances, fewer resources and less energy which minimizes the production cost and waste generation (Kammerer, 2009) which helps in improving their environmental performance. GPrI improves the recyclability and durability of the products,

reduces the quantity of raw materials and removes hazardous materials leading to improved EcP and EnP. Hence, we propose that:

H3. GPrI has a direct positive effect on (a) EcP and (b) EnP.

GPcI is the adoption of manufacturing techniques that help to decline the negative environmental impact during material procurement, production and delivery (Chiou *et al.*, 2011). GPcI reduces the consumption of water and energy and makes the firms' energy and resource efficient (Salvadó *et al.*, 2012) through the application of novel production techniques, which can help the firms improving their economic performance (Rezende *et al.*, 2019). GPcI could help business firms to reduce operating costs through waste recycling and savings of energy (Saunila *et al.*, 2018) leading to improved EcP and EnP. Hence, this study propounds that:

H4. GPcI has a direct positive impact on (a) EcP and (b) EnP.

The success of GPcI depends on GmI, which helps the firms to utilize the resources efficiently (Li *et al.*, 2017). The support of managers is required to implement the innovations and manage the internal environment successfully (Hamel and Prahalad, 1989). Hence, GPcI and GmI could help the firms increase their revenue by reducing the external cost and transferring innovative technology and knowledge (Fernando and Wah, 2017), leading to improved EcP and EnP. Hence, the following hypothesis is propounded based on findings from the literature discussed above:

H5. GmI has a direct positive effect on (a) EcP and (b) EnP.

2.3 The indirect effect of GI (GPrI, GPcI and GmI)

Modern businesses have embraced various strategies, including the enhancement of BDA capabilities, to distinguish themselves from competitors. This approach is particularly relevant in the current market characterized by uncertainty and rapid changes. Xia *et al.* (2020) highlight this strategic adoption of BDA as a means for firms to gain a unique competitive edge. BDA techniques are instrumental in mitigating uncertainties and minimizing failures associated with GI. Zhan *et al.* (2018) emphasize the effectiveness of BDA in providing insights and predictive analytics, which are crucial for successful innovation, particularly in environmentally sustainable practices. The study by Bag *et al.* (2020) demonstrates a significant relation between BDA and enhanced innovative performance, specifically in the development of green products. This finding suggests that BDA not only aids in innovation but also steers firms towards environmentally friendly product innovations. Implementing GI through BDA has been shown to help businesses in reducing waste and production costs, as reported by Sun and Liu (2021). This reduction contributes to improved EcP and EnP, highlighting the dual benefits of BDA in enhancing operational efficiency and environmental stewardship. The fluctuating nature of the market and environmental uncertainties compel businesses to develop and implement procedures that leverage BDA capabilities. This strategic move aims to achieve sustainable environmental and economic performances, recognizing the need for adaptability and resilience in business operations (Lanteri, 2021). Hence, BDA significantly boosts a company's ability to adopt GI across production, process and management. This adoption grants firms a green competitive advantage, enabling them to not only perform better economically but also sustain their operations in an environmentally responsible manner (Alkhatib, 2023). In sum, the pivotal role of BDA in enabling contemporary firms to navigate market uncertainties, innovate sustainably, reduce operational costs and achieve a green competitive advantage, ultimately leading to sustainable economic and environmental performances.

The extant literature has identified the effect of BDA capabilities on economic performance and environmental performance of the firms, but there is a lack of study on the procedures that establish the association between such capabilities and economic performance and environmental performance. BDA capabilities help the firms to implement vital changes in the processes through the GPcI, which helps them to attain sustainable performance. The impact of modern technologies adopted by the industries on their environmental and economic performance mediates through GPcI (Bhatia and Kumar, 2022). GI indirectly influences the association between environmental practices and the competitive advantage of the firms. A study conducted in Jordan found that environmental rules affect firms' performance via GI (Astuti and Datrini, 2021). Fatoki (2021) established that GI influences the environmental orientation of firms. Based on the findings from the literature, we propose that:

- H6. GPcI mediates the positive relation between MC and (a) EcP and (b) EnP.
- H7. GPcI mediates the positive relation between TC and (a) EcP and (b) EnP.
- H8. GPcI mediates the positive relation between MC and (a) EcP and (b) EnP
- H9. GPcI mediates the positive relations between TC and (a) EcP and (b) EnP.
- H10. GMI mediates the positive relations between MC and (a) EcP and (b) EnP.
- H11. GMI mediates the positive relation between TC and (a) EcP and (b) EnP.

2.4 The moderating role of corporate green image (CgI)

The CgI is an important component that improves the green reputation of a business firm within the market (Amores-Salvado' *et al.*, 2014) and attracts new employees and funding sources (Newbury, 2010). The employees of an organization with a green image give maximum effort to develop and adopt innovative approaches, ideas and actions that positively affect the economic and environmental performance of the firm (Song and Yu, 2018). Green image helps companies to enhance their performance on GI which helps the firms to improve economic and environmental performance. A business firm with a higher green reputation may attract more green suppliers and consumers, affecting the firm's economic performance (Tang *et al.*, 2012). Shin and Ki (2019) have identified that green image positively influences the effectiveness of the firms' advertisement process in the USA, which is important for the improvement of economic performance.

Firms with a better green image are more likely to attract funds from public and private financial institutions (Qiu *et al.*, 2020). Firms with a higher green corporate image have a positive image in public (Zhu and Sarkis, 2006), which increases sales and stock prices Waqas *et al.* (2021) have reported that manufacturing firms can increase environmental performance by improving their green image. Kaur and Singh (2020) have reported that business firms with outstanding green image attract more primary resources needed for GI and gives competitive advantage to the firms in India leading to improved environmental and economic performance. Similarly, Soewarno *et al.* (2019) have suggested that Indonesian manufacturing companies improve their green image to acquire environmental legality. Therefore, The CgI helps business firms to improve their reputation, attract financial help and new customers and produce innovative products leading to better economic and environmental performance. Hence, the current research hypothesizes that the higher CgI magnifies the predictive influence of GIs on the economic performance (EcP) and environmental performance (EnP).

- H12a. CgI magnifies the predictive influence of GPcI on EcP, i.e. as the CgI increases, this influence strengthens.

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- H12b.* CgI magnifies the predictive influence of GPcI on EnP, i.e. as the CgI increases, this influence strengthens.
- H12c.* CgI magnifies the predictive influence of GmI on EcP, i.e. as the CgI increases, this influence strengthens.
- H12d.* CgI magnifies the predictive influence of GPrI on EnP, i.e. as the CgI increases, this influence strengthens.
- H12e.* CgI magnifies the predictive influence of GPcI on EcP, i.e. as the CgI increases, this influence strengthens.
- H12f.* CgI magnifies the predictive influence of GmI on EnP, i.e. as the CgI increases, this influence strengthens.
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3. Methodology

3.1 Data collection and procedure

Data was gathered from Indian manufacturing SMEs through surveys filled out by senior managers experienced in or intending to implement BDA and green practices. We used convenience sampling for the survey. Each small and medium-sized enterprise (SME)'s senior managers or higher experience were briefed about the research objective and data collection methods. The study employed a time-lagged method for data collection, conducted at three distinct time intervals. The time-lagged method is characterized by collecting data at multiple points in time, rather than at a single instance. This approach is increasingly prevalent in contemporary research, as it offers several methodological advantages (Mehmood *et al.*, 2022a, 2023b; Shah *et al.*, 2023). The time-lagged technique's popularity in modern research, as stated by Mehmood *et al.* (2023a) and Khan *et al.* (2023a), stems from its ability to facilitate multiple surveys for a single study. This multi-timepoint approach allows for a more dynamic and comprehensive understanding of the research phenomena. One significant advantage of using the time-lagged method is its potential to reduce common method bias (CMB). This bias occurs when data are collected from the same source at one time, leading to inaccuracies due to the source's specific characteristics or circumstances. By collecting data from various sources over time, the study mitigates this risk, enhancing the reliability and validity of the findings. Additionally, the time-lagged method is instrumental in CMB (Mehmood *et al.*, 2023c; Shang *et al.*, 2021, 2022). This type of bias arises when data collection methods or instruments influence the results. By spreading data collection across different time intervals, the method lessens the likelihood that the results are skewed by the peculiarities of a particular data collection instance. This method allows participants the opportunity to analyze and reflect on their behavior before providing their final response, as highlighted by Mehmood *et al.* (2023d). This aspect is crucial because it gives participants time to consider their responses more thoughtfully, possibly leading to more accurate and reflective data (Mehmood *et al.*, 2023e). We performed a preliminary statistical power analysis to determine the necessary sample size for our model. This analysis, based on an expected effect size of 0.150, aimed for 80% statistical power, included six predictors and used a 95% confidence level. It suggested a minimum sample size of 103 (Alzaidi *et al.*, 2023; Mehmood *et al.*, 2022b). Our actual sample size was 950 participants, well above this minimum. This ensures strong model estimation. A further power analysis confirmed the sample's representativeness. To ensure the content validity of the constructs, a pilot test involving 25 participants was conducted on the questionnaire before the main study. The reliability of the scales used in the questionnaire was identified through this test and minor adjustments were made based on feedback from the respondents. This included a corrected item-total correlation analysis and

exploratory factor analysis with varimax rotation and principal components extraction to check for unidimensionality. We also calculated intraclass correlation coefficients. All were above 0.5, indicating good inter-rater agreement. Lastly, Cronbach's alpha values for all scales were above 0.7, meeting Nunnally's (1978) standards for scale reliability.

Three waves of information collection at one month interval were used to minimize the CMB, and the survey was distributed to all the enterprises and representatives (Podsakoff *et al.*, 2003). In the first wave survey (T1), 950 questionnaires were distributed to manufacturing SMEs. Of these, 800 were returned, with 756 being useable responses. During this phase, respondents were asked to provide socioeconomic data and answer questions related to BDA capabilities (MC and TC) and CgI. In the second wave survey (T2), conducted one month later, 756 respondents were approached to report GPRI, GPcI and GmI. From this wave, 647 responses containing useable information were obtained. Finally, during the third-wave survey (T3), respondents were requested to provide information on economic performance and environmental performance. Out of the 647 respondents approached, 417 valid responses were received, indicating a response rate of 41.7%. The distribution of survey respondents of final sample is shown in Table 1. The multivariate analysis of variance approach of Goodman and Blum (1996) was followed to analyze the systematic variations in the responses of those respondents who completed all three waves of survey and those who finished only the first or only the first and second surveys. There was no significant variation in industries, firm size or experience across the groups. Consequently, our study effectively addressed attrition bias, indicating that nonresponse bias does not seem to be a significant concern.

3.2 Measures

Alongside demographic variables, the questionnaire incorporated scales adapted from previous research to measure the constructs under investigation. Respondents rated their responses on a five-point Likert scale, ranging from 1 (indicating “strongly disagree”) to 5 (indicating “strongly agree”). The questionnaires were distributed in both English and Hindi languages. Using the back-translation method by Brislin's (1980), questionnaires were

	Frequency	Percent
<i>Industry</i>		
Energy	20	4.79
General manufacturing	157	37.64
Chemical and miscellaneous products	132	31.65
Electronic and electric equipment	56	13.42
Transportation and vehicle manufacturing	52	12.47
<i>Firm size (in employees)</i>		
Less than 200	76	18.22
201 to 400	201	48.20
401 to 600	110	26.37
601 and above	30	7.19
<i>Experience (in years)</i>		
Less than 5 years	56	13.42
6–10 years	175	41.96
11–20 years	107	25.65
21–30 years	45	10.79
Above 30 years	34	8.15

Table 1.
Distribution of survey
respondent in SME's

Source(s): Authors' own creation

translated from English to Hindi. To assess the BDA (MC) ($\alpha = 0.917$), a 6-item scale was used, drawn from Akter *et al.* (2016). We used a 9-item scale of BDA (TC) ($\alpha = 0.923$) developed by Akter *et al.* (2016). To measure GPrI ($\alpha = 0.831$), a four-item scale was employed, developed by Chiou *et al.* (2011). To measure GPcI ($\alpha = 0.816$), a three-item scale proposed by Chiou *et al.* (2011). To access GmI ($\alpha = 0.857$), a two-item scale was used, adapted by Chiou *et al.* (2011). We used the eight-item scale to measure CgI ($\alpha = 0.881$), developed by Chen (2008). A three-item each scale was employed to estimate EcP ($\alpha = 0.849$) and EnP (0.804), adapted from Chi (2022).

3.3 Common method bias (CMB) and endogeneity

Endogeneity might impact our study. To explore this, we performed a correlation analysis between residuals and predictors, following the method of Khan (2023) and Ali *et al.* (2023). The analysis showed minimal or no correlation between the key variables, indicating that internal endogeneity does not affect our model. In order to mitigate potential CMB concerns, we incorporated procedural remedies recommended by Podsakoff *et al.* (2003). Firstly, we provided participants with the assurance of response anonymity and confidentiality, aiming to minimize social desirability responses. Secondly, we explicitly communicated to the participants that the survey questions had no right or wrong answers and emphasized the confidentiality of their responses. To further examine the presence of CMB, we conducted a CFA on all the variables rated by respondents. However, the single-factor model resulted in a poor fit to the data, as indicated by the following indices: $\chi^2 = 6728.735$, $df = 665$, $\chi^2/df = 10.118$, comparative fit index (CFI) = 0.299, Tucker–Lewis index (TLI) = 0.278 and root mean square error approximation (RMSEA) = 0.211. This suggests that CMB was not a significant issue in our study. Furthermore, to evaluate the measurement context effect, we conducted Harman’s single-factor test, which revealed the presence of multiple distinct factors. Notably, the first factor explained merely 17.69% of the variance, suggesting that CMB was unlikely to pose a significant issue in our survey (Khan *et al.*, 2022, 2023b; Albloushi *et al.*, 2023; Ullah *et al.*, 2021). Furthermore, we employed the marker variable test to identify CMB in our study. The comparison between Model-U (the uncorrected model) and Model-R (the corrected model) revealed no significant differences. This indicates that CMB had minimal, if any, effect on the variable relationships. Consequently, it is improbable that CMB significantly influenced the outcomes of our hypothesis testing. Additionally, we evaluated the sample adequacy using the Kaiser–Meyer–Olkin (KMO) measure, which had a value of 0.893. Since this value is well above the acceptable threshold of 0.80, it confirms that the sample size was appropriate for the study. Furthermore, we checked for multicollinearity concerns by examining the variance inflation factor (VIF) values. All VIF values were found to be below the threshold value of 10, indicating the absence of multicollinearity issues in this study. Furthermore, the measurements’ internal consistency (see Table 2) was examined using internal consistency reliability using composite reliabilities (CRs); all CR values are above the commonly accepted threshold of 0.70 (Hair *et al.*, 2010; Alkatheeri *et al.*, 2023). Convergent validity, measured with average variance extracted (AVE), was tested to examine the construct validity. The AVE values of the sample were higher than the commonly accepted threshold of 0.50 (Hair *et al.*, 2010; Yu *et al.*, 2021; Khan *et al.*, 2022). Based on the results of both AVE and CR values, we can conclude that there are no concerns regarding CMB in our study.

4. Empirical results

4.1 Descriptive statistics

Table 3 presents the standard deviations and correlations values. MC positively correlated with GPrI ($r = 0.337$, $p < 0.01$), GPcI ($r = 0.323$, $p < 0.01$) and GmI ($r = 0.288$, $p < 0.01$). Similarly, TC positively correlated with GPrI ($r = 0.148$, $p < 0.01$), GPcI ($r = 0.204$, $p < 0.01$) and GmI ($r = 0.116$, $p < 0.01$). Furthermore, GPrI positively correlated with EcP ($r = 0.415$,

EJIM	Constructs	Coding	λ	Composite reliabilities	Average variance extracted
	MC			0.921	0.661
		MC 1	0.815		
		MC 2	0.905		
		MC 3	0.849		
		MC 4	0.711		
		MC 5	0.834		
		MC 6	0.748		
	TC			0.928	0.593
		TC 1	0.618		
		TC 2	0.759		
		TC 3	0.782		
		TC 4	0.901		
		TC 5	0.739		
		TC 6	0.773		
		TC 7	0.828		
		TC 8	0.847		
		TC 9	0.638		
	GPrI			0.849	0.589
		GPrI 1	0.715		
		GPrI 2	0.927		
		GPrI 3	0.638		
	GPcI			0.825	0.613
		GPcI 1	0.706		
		GPcI 2	0.749		
		GPcI 3	0.883		
	GmI			0.862	0.759
		GmI 1	0.817		
	CgI	GmI 2	0.922		
				0.904	0.543
		CgI 1	0.721		
		CgI 2	0.618		
		CgI 3	0.736		
		CgI 4	0.859		
		CgI 5	0.751		
		CgI 6	0.683		
		CgI 7	0.854		
		CgI 8	0.637		
	EnP			0.816	0.598
		EnP 1	0.758		
		EnP 2	0.697		
	EcP	EnP 3	0.857		
				0.851	0.661
		EcP 1	0.628		
		EcP 2	0.859		
		EcP 3	0.923		

Table 2. Factor loadings and reliabilities

Note(s): λ = factor loadings; All factor loadings are significant

Source(s): Authors' own creation

$p < 0.01$) and EnP ($r = 0.239, p < 0.01$). GPcI positively correlated with EcP ($r = 0.268, p < 0.01$) and EnP ($r = 0.279, p < 0.01$). GmI positively correlated with EcP ($r = 0.118, p < 0.01$) and EnP ($r = 0.384, p < 0.01$). Additionally, CgI positively correlated with EcP ($r = 0.101, p < 0.05$) and EnP ($r = 0.119, p < 0.01$). Thus, we can advance examine our proposed hypotheses, as these correlations are significantly supported.

Variables	Mean	SD	α	1	2	3	4	5	6	7	8
1. EcP	3.829	0.901	0.849	(0.813)							
2. EnP	4.215	0.957	0.804	0.458**	(0.773)						
3. MC	4.018	0.901	0.917	0.189**	0.517**	(0.813)					
4. TC	3.947	0.854	0.923	0.247**	0.189**	0.481**	(0.770)				
5. GPh	4.357	0.997	0.831	0.415**	0.239**	0.337**	0.148**	(0.767)			
6. GPd	4.144	0.926	0.816	0.268**	0.279**	0.323**	0.204**	0.261**	(0.782)		
7. Gml	3.589	0.793	0.857	0.118**	0.384**	0.288**	0.116*	0.134**	0.199**	(0.871)	
8. Cgl	4.196	0.922	0.891	0.101*	0.119**	0.157**	0.163**	0.131**	0.206**	0.213**	(0.736)
Note(s): Square roots of AVE for each variable are exhibited in parentheses; Cronbach alpha = α ; N = 417; ** $p < 0.01$ and * $p < 0.05$											
Source(s): Authors' own creation											

Table 3.
Correlation matrix

4.2 CFA analysis

Following [Muthén and Muthén \(2012\)](#) recommendations, we used Mplus to perform CFA. Results of CFA (see [Table 4](#)) reveal the eight-factor hypothesized model reasonably better fit the data ($\chi^2/df = 918.234/637 = 1.441$; CFI = 0.987; TLI = 0.971; and RMSEA = 0.037) compared with seven-factor model in which TC, MC, CgI, GPrI, GPcI, EcP and EnP were combined ($\chi^2/df = 1867.324/644 = 2.899$; CFI = 0.771; TLI = 0.729; and RMSEA = 0.103), six-factor model in which CgI, GPrI, GPcI, EnP, EcP and GmI were combined ($\chi^2/df = 2852.179/650 = 4.387$; CFI = 0.642; TLI = 0.607; and RMSEA = 0.112), five-factor model in which GPrI, GPcI, EnP, CgI and GmI were combined ($\chi^2/df = 3420.014/655 = 5.221$; CFI = 0.591; TLI = 0.573; and RMSEA = 0.141), four-factor model in which GPrI, GPcI, GmI and CgI were combined ($\chi^2/df = 4068.278/659 = 6.173$; CFI = 0.515; TLI = 0.503; and RMSEA = 0.154), three-factor model in which GPrI, GPcI and GmI were combined ($\chi^2/df = 5022.299/662 = 7.586$; CFI = 0.499; TLI = 0.467; and RMSEA = 0.167), two-factor model in which CgI and EcP were combined ($\chi^2/df = 6122.491/664 = 9.220$; CFI = 0.341; TLI = 0.312; and RMSEA = 0.184) and single-factor model in which all variables were combined ($\chi^2/df = 6728.735/665 = 10.118$; CFI = 0.299; TLI = 0.278; and RMSEA = 0.211). These results provide evidence of the discriminant validity of the measurement model. Moreover, the factor loadings of the eight constructs were significantly above the threshold value of 0.50, and all items showed significant loadings on their related factors (see [Table 2](#)). Based on these results, our model is deemed suitable for further hypothesis testing.

4.3 Hypotheses testing

Using Mplus ([Muthén and Muthén, 2012](#)), we conducted tests on the fully hypothesized model. The results, presented in [Table 5](#), provide support for [H1a](#), which proposed a positive association between MC and GPrI [unstandardized $\beta = 0.371$, standard error (SE) = 0.031, 95% confidence interval (CI) (0.2427, 0.4189)]. Similarly, [H1b](#), which posited a positive relationship between MC and GPcI [unstandardized $\beta = 0.336$, SE = 0.057, 95% CI (0.2763, 0.3810)], was also supported. Furthermore, the analysis indicated a positive link between MC and GmI [unstandardized $\beta = 0.193$, SE = 0.029, 95% CI (0.1104, 0.2439)], supporting [H1c](#). Regarding [H2a](#), which suggested a positive association between TC and GPrI, the results provided support [unstandardized $\beta = 0.423$, SE = 0.038, 95% CI (0.3552, 0.4928)]. Additionally, [H2b](#), proposing a positive association between TC and GPrI, also received support [unstandardized $\beta = 0.215$, SE = 0.054, 95% CI (0.1020, 0.2696)]. Finally, the analysis revealed a positive relationship between TC and GmI [unstandardized $\beta = 0.180$, SE = 0.044, 95% CI (0.0427, 0.2189)], thereby supporting [H2c](#).

In assessing the impact of GPrI, we found GPrI significantly and positively linked with EcP [unstandardized $\beta = 0.449$, SE = 0.052, 95% CI (0.2931, 0.4973)] and EnP [unstandardized $\beta = 0.516$, SE = 0.047, 95% CI (0.3981, 0.5303)], supporting [H3a](#) and [H3b](#).

Table 4.
Confirmatory factor
analyses and model
fitness

Models	χ^2	<i>df</i>	χ^2/df	$\Delta\chi^2$ (Δdf)	TLI	CFI	RMSEA
8-factor model	918.234	637	1.441		0.971	0.987	0.037
7-factor model	1867.324	644	2.899	949.09 (7)	0.729	0.771	0.103
6-factor model	2852.179	650	4.387	1933.945 (13)	0.607	0.642	0.112
5-factor model	3420.014	655	5.221	2501.78 (18)	0.573	0.591	0.141
4-factor model	4068.278	659	6.173	3150.044 (22)	0.503	0.515	0.154
3-factor model	5022.299	662	7.586	4104.065 (25)	0.467	0.499	0.167
2-factor model	6122.491	664	9.220	5204.263 (27)	0.312	0.341	0.184
1-factor model	6728.735	665	10.118	5810.501 (28)	0.278	0.299	0.211

Source(s): Authors' own creation

Hypotheses	Unstandardized coefficients (β)	95% CI	S.E.	p-value
<i>Direct effects</i>				
H1a: MC $\rightarrow$ GPrI	0.371**	[0.2427, 0.4189]	0.031	0.001
H1b: MC $\rightarrow$ GPcI	0.336**	[0.2763, 0.3810]	0.057	0.004
H1c: MC $\rightarrow$ GmI	0.193***	[0.1104, 0.2439]	0.031	0.021
H2a: TC $\rightarrow$ GPrI	0.423***	[0.3552, 0.4928]	0.027	0.001
H2b: TC $\rightarrow$ GPcI	0.215**	[0.1020, 0.2696]	0.054	0.032
H2c: TC $\rightarrow$ GmI	0.180**	[0.0427, 0.2189]	0.024	0.017
H3a: GPrI $\rightarrow$ EcP	0.449**	[0.2931, 0.4973]	0.062	0.005
H3b: GPrI $\rightarrow$ EnP	0.516**	[0.3981, 0.5303]	0.047	0.042
H4a: GPcI $\rightarrow$ EcP	0.174**	[0.0952, 0.2270]	0.027	0.007
H4b: GPcI $\rightarrow$ EnP	0.541**	[0.3780, 0.5897]	0.036	0.031
H5a: GmI $\rightarrow$ EcP	0.537**	[0.3901, 0.5872]	0.053	0.028
H5b: GmI $\rightarrow$ EnP	0.579**	[0.4169, 0.6081]	0.047	0.008
<i>Moderating effects</i>				
H12a: CgI * GPrI $\rightarrow$ EcP	0.428**	[0.3598, 0.4803]	0.029	0.001
H12b: CgI * GPrI $\rightarrow$ EnP	0.183**	[0.0088, 0.2279]	0.037	0.002
H12c: CgI * GPcI $\rightarrow$ EcP	0.270**	[0.1054, 0.3003]	0.054	0.005
H12d: CgI * GPcI $\rightarrow$ EnP	0.262**	[0.1221, 0.3254]	0.028	0.017
H12e: CgI * GmI $\rightarrow$ EcP	0.324**	[0.2537, 0.3967]	0.031	0.005
H12f: CgI * GmI $\rightarrow$ EnP	0.351**	[0.3031, 0.4253]	0.058	0.023

Note(s): ** $p < 0.01$; *** $p < 0.001$; BDA management capability = MC, BDA talent capability = TC; corporate green image = CgI; green product innovation = GPrI; green process innovation = GPcI; green managerial innovation = GmI; economic performance = EcP and environmental performance = EnP

Source(s): Authors' own creation

Table 5.
Results of direct and moderating hypothesis

Similarly, considering the impact of GPcI, we found GPcI significantly related with EcP [unstandardized $\beta = 0.174$, SE = 0.027, 95% CI (0.0952, 0.2270)] and EnP [unstandardized $\beta = 0.541$, SE = 0.036, 95% CI (0.3780, 0.5897)], supporting H4a and H4b. Furthermore, the results have exhibited that GmI is significantly related with EcP [unstandardized $\beta = 0.537$, SE = 0.053, 95% CI (0.3901, 0.5872)] and EnP [unstandardized $\beta = 0.579$, SE = 0.047, 95% CI (0.4169, 0.6081)], supporting H5a and H5b.

4.4 Analysis of corporate green image (CgI) as a moderator

H12a proposes that CgI moderates the positive association between GPrI and EcP, indicating that a high level of CgI strengthens the positive influence of GPrI on EcP. This hypothesis received support as the interaction term (CgI * GPrI) showed significance ($\beta = 0.428$, $p < 0.01$) (see Table 5). The plotted interaction (CgI * GPrI) (see Figure 3) further revealed a stronger link with a high level of CgI, supporting H12a. In a parallel manner, H12b posits that CgI acts as a moderator in the positive link between GPrI and EnP, signifying that a heightened CgI level amplifies the beneficial influence of GPrI on EnP. Substantiating this hypothesis, the interaction term (CgI * GPrI) displayed statistical significance ($\beta = 0.183$, $p < 0.01$). The graphical representation of this interaction (CgI * GPrI) can be observed in Figure 4, affirming that the connection is more pronounced when CgI is at a higher level, thus supporting H12b. Transitioning to H12c, it suggests that CgI plays a moderating role in the positive relationship between GPcI and EcP, indicating that a heightened CgI level bolsters the positive impact of GPcI on EcP. Supporting this hypothesis, the interaction term (CgI * GPcI) exhibited significance ($\beta = 0.270$, $p < 0.01$). The visual representation of this interaction (CgI * GPcI) can be found in Figure 5, affirming that the association is more robust when CgI is elevated, thus supporting H12c. Similarly, H12d postulates that CgI moderates the positive connection between GPcI and EnP, signifying that a high level of CgI intensifies the positive

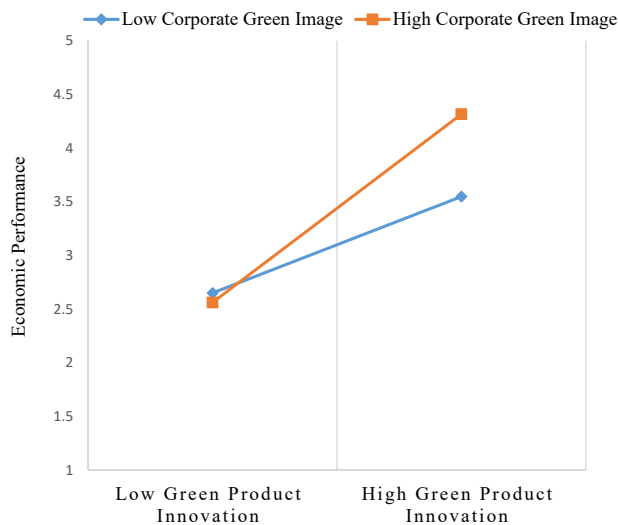


Figure 3.
Interactive effects of
green product
innovation and
corporate image on
economic performance

Source(s): Authors' own creation

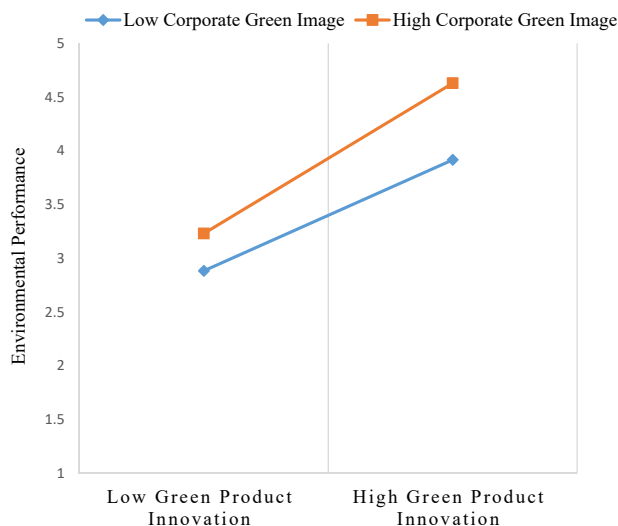


Figure 4.
Interactive effects of
green product
innovation and
corporate image on
environmental
performance

Source(s): Authors' own creation

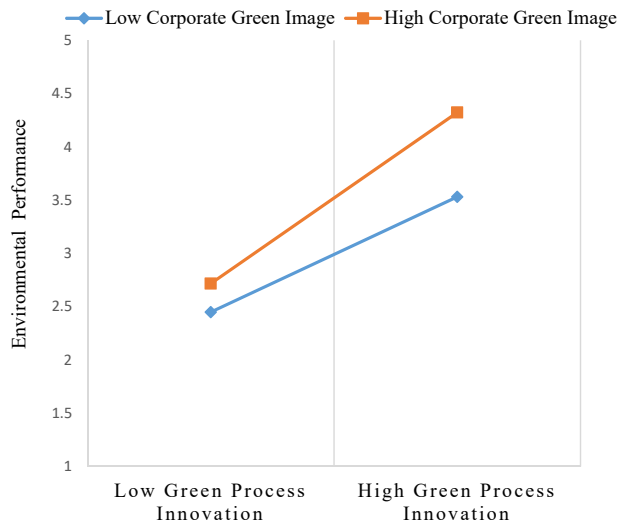
effect of GPcI on EnP. Supporting this hypothesis, the interaction term (CgI * GPcI) reached statistical significance ($\beta = 0.262, p < 0.05$). The graphical representation of this interaction (CgI * GPcI) is depicted in [Figure 6](#), showing a stronger association with a high CgI level and endorsing [H12d](#).

Furthermore, [H12e](#) proposes that CgI acts as a moderator in the positive association between GmI and EcP, indicating that a high level of CgI enhances the positive influence of



Source(s): Authors' own creation

Figure 5.
Interactive effects of
green process
innovation and
corporate image on
economic performance



Source(s): Authors' own creation

Figure 6.
Interactive effects of
green process
innovation and
corporate image on
environmental
performance

GmI on EcP. Supporting this hypothesis, the interaction term (CgI * GmI) achieved statistical significance ($\beta = 0.324, p < 0.01$), as shown in Table 5. The graphical representation of this interaction (CgI * GmI) is presented in Figure 7, further affirming a stronger connection with a high CgI level and supporting H12e. Similarly, H12f suggests that CgI plays a moderating role in the positive linkage between GmI and EnP, implying that a high level of CgI magnifies the positive impact of GmI on EnP. Supporting this hypothesis, the interaction term (CgI * GmI) was significant ($\beta = 0.351, p < 0.05$). The plotted interaction (CgI * GmI) (see Figure 8) confirms that the link is stronger with a high level of CgI, supporting H12f.



Figure 7.
Interactive effects of
green managerial
innovation and
corporate image on
economic performance

Source(s): Authors' own creation



Figure 8.
Interactive effects of
green managerial
innovation and
corporate image on
environmental
performance

Source(s): Authors' own creation

4.5 Analysis of GI (GPrI, GPcI, and GmI) as a mediator

To examine the mediation hypotheses (see Table 6), we utilized Hayes' (2018) PROCESS macro and ran Model-4 with 5,000 bootstrapped samples. This analysis aimed to explore the indirect effects of GPrI, GPcI and GmI on BDA capabilities (MC and TC), as well as their impact on EcP and EnP. The results indicated that the indirect influence of GPrI through MC on EcP [indirect effect = 0.1621, 95% CI (0.0081, 0.2027)] and MC on EnP [indirect effect = 0.1869, 95% CI (0.0283, 0.1493)] was statistically significant; hence H6a and H6b were supported. Similarly, the results showed that the indirect influence of GPrI through TC on

								Harnessing big data analytics in manufacturing SME
IV	MV	DV	Unstandardized effect of IV on M (a)	Unstandardized effect of M on DV (b)	Indirect effect (a*b)	95% CI	Supported	
<i>H6a: MC → GPrI → EcP</i>								

Table 6.
Results of the indirect effects

EcP [indirect effect = 0.1841, 95% CI (0.0112, 0.2126)] and TC on EnP [indirect effect = 0.2126, 95% CI (0.1102, 0.2867)] was statistically significant; hence [H7a](#) and [H7b](#) were supported.

The results have revealed a significant indirect relationship of GPcI between MC and EcP [indirect effect = 0.0519, 95% CI (0.0056, 0.1809)] and MC on EnP [indirect effect = 0.1628, 95% CI (0.0806, 0.2065)] was statistically significant; therefore, we accept [H8a](#) and [H8b](#). Similarly, the indirect relationship of GPcI between TC and EcP [indirect effect = 0.0326, 95% CI (0.0069, 0.1675)] and TC on EnP [indirect effect = 0.1024, 95% CI (0.0586, 0.1985)] was statistically significant; therefore, we accept [H9a](#) and [H9b](#) were supported.

Moreover, the study's results provided evidence supporting [H10a](#) and [H10b](#), as the results revealed a statistically significant indirect effect of GmI on EcP and EnP through MC. The estimated indirect effects were [0.1087, 95% CI (0.0716, 0.2005)] for EcP and [0.1144, 95% CI (0.0292, 0.1966)] for EnP. Similarly, [H11a](#) and [H11b](#) received empirical support, as the results

showed a significant indirect influence of GmI on EcP and EnP through TC. The estimated indirect effects were [0.0948, 95% CI (0.0073, 0.1505)] for EcP and [0.0997, 95% CI (0.0100, 0.2006)] for EnP.

5. Discussion

This study explores the influence of BDA capabilities on GI (GPrI, GPcI and GmI) and examines the mediating impact of GPrI, GPcI and GmI between BDA capabilities and economic (EcP) and environmental (EnP) performance in manufacturing SMEs. This research also analyses the moderating role of CgI between GI (GPrI, GPcI and GmI) and EcP and EnP. The proposed relationship between the constructs was analyzed using the DCV paradigm as conceptual framework. The Indian government is committed to solving environmental issues by formulating strict production rules and industry regulations. This would lead the Indian manufacturing SMEs to make their products and mode of production environmentally friendly innovative technologies, including BDA and GI, to attain EcP and EnP and improve their reputation in the market. The results indicated that BDA capabilities including MC and TC of a firm improves its EcP and EnP through GI.

The study produced several significant outcomes and validated all proposed hypotheses. The findings indicated that the constructs comprising BDA capabilities, GI and CgI significantly improves the EcP and EnP of Indian manufacturing SMEs. This supports the findings of [AlKhatib \(2022\)](#) who has demonstrated that BDA capabilities play a critical role in improving the environmental performance of firms. Manufacturing SMEs can discover the information hidden inside big data that can be applied in the development and implementation of GI practices helping them in improving their economic and environmental performance. BDA capabilities including the MC and TC can be utilized by the manufacturing SMEs in understanding the customer and market demands needed for enhancing the operational performance to improve their EcP and EnP.

The findings of the study confirm that the manufacturing industries can enhance their GI by improvement of BDA capabilities. The relation between GI and BDA capabilities can be accurately explained using DCV paradigm, which states that the firms can create new capabilities through optimal exploitation of their dynamic capabilities leading to improved environmental and economic performance. The exploitation of the big data capabilities by the firms will improve their GI which can be crucial for improving the degree of innovation. Hence, BDA capabilities can be considered as an important asset for reducing and recycling of wastes and improved environmental and economic performance ([AlKhatib, 2022](#)). Moreover, earlier studies have also confirmed that development of GI is crucial for economic performance and environmental performance as it helps in reducing waste, pollution and costs. The firms with CgI can gain more advantage by investing in GI as the results indicated that CgI positively moderates the relationship between GI (GPrI, GPcI and GmI) and economic and environmental performance. The CgI helps a firm in creating a positive image in the market and customers consider their products reliable that gives them an advantage over the competitors.

Eventually, this research suggests that enhancement BDA capabilities by the firms will improve their organizational performance leading to improved economic performance and environmental performance. Our model and findings give empirical evidence that through appropriate analytical tools the big data can be a useful resource for the manufacturing SMEs to attain economic and environmental performance. The findings also suggest that BDA capabilities are critical for the development of innovative environment in the firm and GI in management, process and product can provide economic and environmental performance to the firms. Thus, the SMEs who want to attain performance and environmental performance must develop their GI capabilities through investing in BDA capabilities.

5.1 Theoretical implications

The findings obtained from the empirical data show that MC and TC have a significant positive effect on GPrI, GPcI and GmI. Previous research has also discovered the significant positive impact of BDA capabilities on innovation and the learning process (Bag *et al.*, 2020). However, none of the earlier research has individually established the association between MC:TC on GPrI, GPcI and GmI. The above finding implies that the MC and TC are valuable capabilities that the Indian manufacturing SMEs could adopt to make GI in their process, product and management to enhance economic and environmental performance. Further, the current research also verifies the link between GPrI, GPcI, GmI and economic and environmental performance. The findings indicate that all three categories of GI have a significant favorable influence on economic and environmental performance. Therefore, manufacturing industries can improve economic and environmental performance with the proper application of GI in all departments. Moreover, Zameer *et al.* (2020) have claimed that firms may build their competitive advantage through green production. Hence, GI would help manufacturing SMEs improve their EcP and EnP.

This research also confirms that the MC and TC influence EcP and EnP through GI. The manufacturing SMEs may attain and improve their economic and environmental performance by adopting BDA capabilities in GI of products, processes and management. The BDA capabilities support the development of green talent and skills in the employee and managers of a business firm which lead to GI (Akter *et al.*, 2016). The analysis of the moderating influence of CgI indicated that it could help manufacturing SMEs convert the benefits obtained through GI in improving economic performance and environmental performance. The CgI of SMEs works as a catalyst for GI and increases environmental performance of manufacturing industries. Thus, manufacturing firms with CgI have better chances to enhance their economic and environmental performance through proper adoption and implementation of GPrI, GmI and GPcI.

5.2 Managerial implications

The findings of this research offer a variety of insights that senior managers in manufacturing industries can utilize to improve both economic and environmental performance. The BDA approach encompasses novel resources, tools and operating techniques and advanced technology, which business firms adopt to identify novel ideas for effective and efficient big data handling. The approach would help manufacturing SMEs improve their performance and sustain them for longer. The present research outcomes demonstrate the influence of MC and TC on EcP and EnP through GI as a mediating factor and Analysis of corporate green image (CgI) as a moderating factor. The manufacturing industries with BDA capabilities and GCI would be more capable of promoting GI in product, process and management to improvement of economic and environmental performance. The success of MC and TC in promoting the GI and EcP and EnP depends on the attitude of the members of business firms towards knowledge transfer with each other. Therefore, the higher-level management of the manufacturing SMEs should formulate policies on adopting and using MC and TC and encourage the members to share the knowledge to promote GI for achieving economic and environmental performance. It would help the manufacturing SMEs formulate novel GI ideas to attain economic and environmental performance, which other firms cannot imitate.

Additionally, the research outcomes disclosed that manufacturing firms could enhance their CgI and attain economic and environmental performance by making their products and services green through adopting green processes, products and managerial innovations. The study's findings reveal that CgI is a strong catalyst controlling GI and economic and environmental performance relationship. Thus, through CgI, the manufacturing SMEs would enhance their green reputation, differentiate their products and services and green image

through GI of products, processes and management. Although the management of firms has realized the importance of improved economic and environmental performance, numerous firms have still not applied GI in product, process and management. This requires enormous capital investment, time and competencies to promote and adopt BDA capabilities for GI to improve economic performance and environmental performance of manufacturing firms. The managers should encourage adopting GI for products, processes and management using BDA capabilities to improve the performance of the business firms. Therefore, we recommend that Indian manufacturing SMEs invest in BDA capabilities and GI to enhance EcP and EnP.

5.3 Limitations and direction for future research

This study has some limitations and should be addressed in upcoming research. The study outcomes are based on a comparatively small sample size collected using the time-lagged design from the Indian manufacturing SMEs. Hence, the results should be verified by conducting research in other developing countries. The relation between BDA capabilities and economic and environmental performance is conceptualized using the DCV paradigm, which may be examined by future works using more complex conceptual models. Moreover, future studies may also identify the impact of BDA technological capabilities on GPrI, GPcI, GmI and economic and environmental performance. Future works could also analyze and validate the influence of green production on employment development and green learning innovation on sustainable economic and environmental performance. Certain critical issues, such as the analytics climate and privacy concerns were not addressed in this study but present potential avenues for future research. [Ekbias et al. \(2015\)](#) characterized big data as “dark data,” highlighting the necessity for its investigation through a meaningful and balanced approach. This necessitates the application of appropriate talent, technology and strategic methods to ensure a comprehensive understanding and responsible utilization of big data. Future studies can also use other pertinent constructs not examined in earlier literature. Besides, the study’s findings cannot be generalized for the manufacturing SMEs in different developing countries unless it is not validated by the studies conducted in other developing countries using identical sample sizes from the manufacturing firms.

5.4 Conclusion

The study’s conclusion emphasizes the increasing importance of BDA capabilities in manufacturing firms for enhancing economic and environmental performance. It addresses a gap in existing literature by uncovering the mechanisms through which BDA capabilities influence these performance aspects. The study reveals the indirect role of GI and the moderating influence of CgI in the relationship between BDA capabilities, specifically MC and TC and economic and environmental performance. Data collected from 417 manufacturing firms using a time-lagged design provided empirical evidence that both MC and TC significantly impact GI. GI, in turn, plays a crucial mediating role between BDA and the economic and environmental performance of firms. Furthermore, the study found that CgI enhances the effect of GI on these performance metrics, suggesting a synergistic interaction between CgI and innovation practices. These findings hold substantial theoretical and practical implications for manufacturing SMEs and policymakers, offering a nuanced understanding of the pathways through which BDA capabilities can be leveraged for better economic and environmental outcomes. This study notably contributes to the literature on BDA by empirically demonstrating the effects of MC and TC on improving the EcP and EnP of manufacturing firms. It accomplishes this through the indirect impact of GIs and the moderating effect of CgI, thus expanding the DCV paradigm.

References

- Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R. and Childe, S.J. (2016), "How to improve organization performance using big data analytics capability and business strategy alignment?", *International Journal of Production and Economics*, Vol. 182, pp. 113-131, doi: [10.1016/j.ijpe.2016.08.018](https://doi.org/10.1016/j.ijpe.2016.08.018).
- Albloushi, B., Alharmoodi, A., Jabeen, F., Mehmood, K. and Farouk, S. (2023), "Total quality management practices and corporate sustainable development in manufacturing companies: the mediating role of green innovation", *Management Research Review*, Vol. 46 No. 1, pp. 20-45, doi: [10.1108/mrr-03-2021-0194](https://doi.org/10.1108/mrr-03-2021-0194).
- Ali, A., Wang, H., Gong, M. and Mehmood, K. (2023), "Conservation of resources theory perspective of social media ostracism influence on lurking intentions", *Behaviour and Information Technology*, Vol. 43, pp. 1-18, doi: [10.1080/0144929x.2022.2159873](https://doi.org/10.1080/0144929x.2022.2159873).
- Alkathetri, H.B., Jabeen, F., Mehmood, K. and Santoro, G. (2023), "Elucidating the effect of information technology capabilities on organizational performance in UAE: a three-wave moderated-mediation model", *International Journal of Emerging Markets*, Vol. 18 No. 10, pp. 3913-3934, doi: [10.1108/ijem-08-2021-1250](https://doi.org/10.1108/ijem-08-2021-1250).
- Alkhatib, A.W. (2022), "Can big data analytics capabilities promote a competitive advantage? Green radical innovation, green incremental innovation and data-driven culture in a moderated mediation model", *Business Process Management*, Vol. 28 No. 4, pp. 1025-1046, doi: [10.1108/bpmj-05-2022-0212](https://doi.org/10.1108/bpmj-05-2022-0212).
- Alkhatib, A.W. (2023), "Fostering green innovation: the roles of big data analytics capabilities and green supply chain integration", *European Journal of Innovation Management*. doi: [10.1108/EJIM-09-2022-0491](https://doi.org/10.1108/EJIM-09-2022-0491).
- Alzaidi, S.M., Iyanna, S., Jabeen, F. and Mehmood, K. (2023), "Understanding employees' voluntary pro-environmental behavior in public organizations—an integrative theory approach", *Social Responsibility Journal*, Vol. 19 No. 8, pp. 1466-1489, doi: [10.1108/srj-04-2022-0176](https://doi.org/10.1108/srj-04-2022-0176).
- Amores-Salvadó, J., Martín-de Castro, G. and Navas-López, J.E. (2014), "Green corporate image: moderating the connection between environmental product innovation and firm performance", *Journal of Cleaner Production*, Vol. 83, pp. 356-365, doi: [10.1016/j.jclepro.2014.07.059](https://doi.org/10.1016/j.jclepro.2014.07.059).
- Asadi, S., Pourhashemi, S.O., Nilashi, M., Abdullah, R., Samad, S., Yadegaridehkordi, E., Aljojo, N. and Razali, N.S. (2020), "Investigating influence of green innovation on sustainability performance: a case on Malaysian hotel industry", *Journal of Cleaner Production*, Vol. 258, 120860.
- Astuti, P. and Datrini, L. (2021), "Green competitive advantage: examining the role of environmental consciousness and green intellectual capital", *Management Science Letters*, Vol. 11 No. 4, pp. 1141-1152.
- Aydiner, A.S., Tatoglu, E., Bayraktar, E., Zaim, S. and Delen, D. (2019), "Business analytics and firm performance: the mediating role of business process performance", *Journal of Business Research*, Vol. 96, pp. 228-237, doi: [10.1016/j.jbusres.2018.11.028](https://doi.org/10.1016/j.jbusres.2018.11.028).
- Bag, S., Wood, L.C., Xu, L., Dhamija, P. and Kayikci, Y. (2020), "Big data analytics as an operational excellence approach to enhance sustainable supply chain performance", *Resources Conservation and Recycling*, Vol. 153, 104559, doi: [10.1016/j.resconrec.2019.104559](https://doi.org/10.1016/j.resconrec.2019.104559).
- Barton, D. and Court, D. (2012), "Making advanced analytics work for you", *Harvard Business Review*, Vol. 90 No. 10, pp. 78-83.
- Bhatia, M.S. and Kumar, S. (2022), "Linking stakeholder and competitive pressure to Industry 4.0 and performance: mediating effect of environmental commitment and green process innovation", *Business Strategy and the Environment*, Vol. 31 No. 5, pp. 1905-1918, doi: [10.1002/bse.2989](https://doi.org/10.1002/bse.2989).
- Brislin, R.W. (1980), "Translation and content analysis of oral and written materials", in Triandis, H.C. and Berry, J.W. (Eds), *Handbook of Cross-Cultural Psychology: Methodology*, Allyn Bacon, Boston, pp. 339-444.
- Capurro, R., Fiorentino, R., Garzella, S. and Giudici, A. (2021), "Big data analytics in innovation processes: which forms of dynamic capabilities should be developed and how to embrace

- digitization?", *European Journal of Innovation Management*, Vol. 25 No. 6, pp. 273-294, doi: [10.1108/ejim-05-2021-0256](https://doi.org/10.1108/ejim-05-2021-0256).
- Chen, Y.S. (2008), "The driver of green innovation and green image-green core competence", *Journal of Business Ethics*, Vol. 81 No. 3, pp. 531-543, doi: [10.1007/s10551-007-9522-1](https://doi.org/10.1007/s10551-007-9522-1).
- Chen, Y.S. (2011), "Green organizational identity: sources and consequence", *Management Decision*, Vol. 49 No. 3, pp. 384-404, doi: [10.1108/00251741111120761](https://doi.org/10.1108/00251741111120761).
- Chen, Y.S. and Chang, C.H. (2013), "The determinants of green product development performance: green dynamic capabilities. Green transformational leadership, and green creativity", *Journal of Business Ethics*, Vol. 116 No. 1, pp. 107-119, doi: [10.1007/s10551-012-1452-x](https://doi.org/10.1007/s10551-012-1452-x).
- Chen, Y.S., Lai, S.B. and Wen, C.T. (2006), "The influence of green innovation performance on corporate advantage in Taiwan", *Journal of Business Ethics*, Vol. 67 No. 4, pp. 331-339, doi: [10.1007/s10551-006-9025-5](https://doi.org/10.1007/s10551-006-9025-5).
- Chi, N.T.K. (2022), "Driving factors for green innovation in agricultural production: an empirical study in an emerging economy", *Journal of Cleaner Production*, Vol. 368, 132965.
- Chiou, T.Y., Chan, H.K., Lettice, F. and Chung, S.H. (2011), "The influence of greening the suppliers and green innovation on environmental performance and competitive advantage in Taiwan", *Transportation Research Part E Logistic Transportation Review*, Vol. 47 No. 6, pp. 822-836, doi: [10.1016/j.tre.2011.05.016](https://doi.org/10.1016/j.tre.2011.05.016).
- Columbus, L. (2014), "84% of enterprises see big data analytics changing their industries' competitive landscapes in the next year", *Forbes*, available at: <https://www.forbes.com/sites/louiscolumbus/2014/10/19/84-of-enterprises-see-big-data-analytics-changing-their-industries-competitive-landscapes-in-the-next-year/?sh=3f5a6c1a17de>
- Dang, V.T. and Wang, J. (2022), "Building competitive advantage for hospitality companies: the roles of green innovation strategic orientation and green intellectual capital", *International Journal of Hospitality Management*, Vol. 102, 103161.
- Ekbia, H., Mattioli, M., Kouper, I., Arave, G., Ghazinejad, A., Bowman, T., Suri, V.R., Tsou, A., Weingart, S. and Sugimoto, C.R. (2015), "Big data, bigger dilemmas: a critical review", *Journal of the Association for Information Science and Technology*, Vol. 66 No. 8, pp. 1523-1545, doi: [10.1002/asi.23294](https://doi.org/10.1002/asi.23294).
- Fatoki, O. (2021), "Environmental orientation and green competitive advantage of hospitality firms in South Africa: mediating effect of green innovation", *Journal of Open Innovation: Technology, Market, and Complexity*, Vol. 7 No. 4, p. 223, doi: [10.3390/joitmc7040223](https://doi.org/10.3390/joitmc7040223).
- Fernando, Y. and Wah, W.X. (2017), "The impact of eco-innovation drivers on environmental performance: empirical results from the green technology sector in Malaysia", *Sustainable Production and Consumption*, Vol. 12, pp. 27-43, doi: [10.1016/j.spc.2017.05.002](https://doi.org/10.1016/j.spc.2017.05.002).
- Ge, B., Yang, Y., Jiang, D., Gao, Y., Du, X. and Zhou, T. (2018), "An empirical study on green innovation strategy and sustainable competitive advantages: path and boundary", *Sustainability*, Vol. 10 No. 10, p. 3631.
- Goodman, J.S. and Blum, T.C. (1996), "Assessing the non-random sampling effects of subject attrition in longitudinal research", *Journal of Management*, Vol. 22 No. 4, pp. 627-652, doi: [10.1177/014920639602200405](https://doi.org/10.1177/014920639602200405).
- Gürlek, M. and Tuna, M. (2018), "Reinforcing competitive advantage through green organizational culture and green innovation", *Service Industries Journal*, Vol. 38 Nos 7-8, pp. 467-491, doi: [10.1080/02642069.2017.1402889](https://doi.org/10.1080/02642069.2017.1402889).
- Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. and Tatham, R.L. (2010), *Multivariate Data Analysis: A Global Perspective*, 7th ed., Pearson, Upper Saddle River, NJ.
- Hamel, G. and Prahalad, C.K. (1989), "Strategic intent", *Harvard Business Review*, Vol. 67 No. 3, pp. 63-76.
- Hayes, A.F. (2018), "Partial, conditional, and moderated moderated mediation: quantification, inference, and interpretation", *Communication Monographs*, Vol. 85 No. 1, pp. 4-40, doi: [10.1080/03637751.2017.1352100](https://doi.org/10.1080/03637751.2017.1352100).

-
- Kammerer, D. (2009), "The effects of customer benefit and regulation on environmental product innovation", *Ecological Economics*, Vol. 68 Nos 8-9, pp. 2285-2295, doi: [10.1016/j.ecolecon.2009.02.016](https://doi.org/10.1016/j.ecolecon.2009.02.016).
- Kaur, A. and Singh, B. (2020), "Disentangling the reputation–performance paradox: indian evidence", *Journal of Indian Business Research*, Vol. 12 No. 2, pp. 153-167, doi: [10.1108/jibr-02-2018-0081](https://doi.org/10.1108/jibr-02-2018-0081).
- Khan, A.N. (2023), "Elucidating the effects of environmental consciousness and environmental attitude on green travel behavior: moderating role of green self-efficacy", *Sustainable Development*. doi: [10.1002/sd.2771](https://doi.org/10.1002/sd.2771).
- Khan, A.N., Mehmood, K. and Khan, N.A. (2022), "How STEM-based CI and leadership support can turn possibly bad situations into opportunities?", *Academy of Management Proceedings*, Academy of Management, Briarcliff Manor, NY, Vol. 2022 No. 1, 12293.
- Khan, A.N., Jabeen, F., Mehmood, K., Soomro, M.A. and Bresciani, S. (2023a), "Paving the way for technological innovation through adoption of artificial intelligence in conservative industries", *Journal of Business Research*, Vol. 165, 114019, doi: [10.1016/j.jbusres.2023.114019](https://doi.org/10.1016/j.jbusres.2023.114019).
- Khan, A.N., Khan, N.A. and Mehmood, K. (2023b), "Exploring the relationship between learner proactivity and social capital via online learner interaction: role of perceived peer support", *Behaviour and Information Technology*, Vol. 42 No. 11, pp. 1818-1832, doi: [10.1080/0144929x.2022.2099974](https://doi.org/10.1080/0144929x.2022.2099974).
- Kim, N. and Srivastava, R.K. (1998), "Managing intraorganizational diffusion of technological innovations", *Industrial Marketing Management*, Vol. 27 No. 3, pp. 229-246.
- Lanteri, A. (2021), "Strategic drivers for the fourth industrial revolution", *Thunderbird International Business Review*, Vol. 63 No. 3, pp. 273-283, doi: [10.1002/tie.22196](https://doi.org/10.1002/tie.22196).
- Lavalle, S., Lesser, E., Shockley, R., Hopkins, M.S. and Kruschwitz, N. (2011), "Big data, analytics and the path from insights to value", *MIT Sloan Management Review*, Vol. 52, pp. 21-32.
- Li, D., Zheng, M., Cao, C., Chen, X., Ren, S. and Huang, M. (2017), "The impact of legitimacy pressure and corporate profitability on green innovation: evidence from China top 100", *Journal of Cleaner Production*, Vol. 141, pp. 41-49, doi: [10.1016/j.jclepro.2016.08.123](https://doi.org/10.1016/j.jclepro.2016.08.123).
- Lozada, N., Arias-Perez, J. and Perdomo-Charry, G. (2019), "Big data analytics capability and co-innovation: an empirical study", *Heliyon*, Vol. 5 No. 10, e02541, doi: [10.1016/j.heliyon.2019.e02541](https://doi.org/10.1016/j.heliyon.2019.e02541).
- Malik, A.R. and Singh, P. (2014), "High potential' programs: let's hear it for 'B' players", *Human Resources Management Review*, Vol. 24 No. 4, pp. 330-346, doi: [10.1016/j.hrmr.2014.06.001](https://doi.org/10.1016/j.hrmr.2014.06.001).
- Marshall, A., Mueck, S. and Shockley, R. (2015), "How leading organizations use big data and analytics to innovate", *Strategy Leaders*, Vol. 43 No. 5, pp. 32-39, doi: [10.1108/sl-06-2015-0054](https://doi.org/10.1108/sl-06-2015-0054).
- Mehmood, K., Jabeen, F., Iftikhar, Y., Yan, M., Khan, A.N., AlNahyan, M.T., Alkindi, H.A. and Alhammadi, B.A. (2022a), "Elucidating the effects of organisational practices on innovative work behavior in UAE public sector organisations: the mediating role of employees' wellbeing", *Applied Psychology: Health and Well-Being*, Vol. 14 No. 3, pp. 715-733, doi: [10.1111/aphw.12343](https://doi.org/10.1111/aphw.12343).
- Mehmood, K., Jabeen, F., Hui, Z., Iyanna, S., Zhang, C., Iftikhar, Y. and Kalia, P. (2022b), "Socially responsible plastic consumption behavior: a multi-wave study of UAE", *Academy of Management Proceedings*, Academy of Management, Briarcliff Manor, NY, Vol. 2022 No. 1, 14620.
- Mehmood, K., Jabeen, F., Rehman, H., Iftikhar, Y. and Khan, N.A. (2023a), "Understanding the boosters of employees' voluntary pro-environmental behavior: a time-lagged investigation", *Environment, Development and Sustainability*, pp. 1-23, doi: [10.1007/s10668-023-03121-3](https://doi.org/10.1007/s10668-023-03121-3).
- Mehmood, K., Iftikhar, Y., Khan, A.N. and Kwan, H.K. (2023b), "The nexus between high-involvement work practices and employees' proactive behavior in public service organizations: a time-lagged moderated-mediation model", *Psychology Research and Behavior Management*, Vol. 16, pp. 1571-1586, doi: [10.2147/prbm.s399292](https://doi.org/10.2147/prbm.s399292).
- Mehmood, K., Zia, A., Alkatheeri, H.B., Jabeen, F. and Zhang, H. (2023c), "Resource-based view theory perspective of information technology capabilities on organizational performance in hospitality

- firms: a time-lagged investigation”, *Journal of Hospitality and Tourism Technology*, Vol. 14 No. 5, pp. 701-716, doi: [10.1108/jhtt-05-2021-0149](https://doi.org/10.1108/jhtt-05-2021-0149).
- Mehmood, K., Jabeen, F., Al Hammadi, K.I.S., Al Hammadi, A., Iftikhar, Y. and AlNahyan, M.T. (2023d), “Disentangling employees’ passion and work-related outcomes through the lens of cross-cultural examination: a two-wave empirical study”, *International Journal of Manpower*, Vol. 44 No. 1, pp. 37-57, doi: [10.1108/ijm-11-2020-0532](https://doi.org/10.1108/ijm-11-2020-0532).
- Mehmood, K., Iftikhar, Y., Hui, Z., Rehman, H., Zhang, C. and Jabeen, F. (2023e), “Managers’ perceptions of and behavioral responses to COVID-19 threats: a role of ethical leadership”, *Academy of Management Proceedings*, Academy of Management, Briarcliff Manor, NY, Vol. 2023 No. 1, 17423.
- Mehmood, K., Kiani, A. and Rashid, M. (2023f), “Is data the key to sustainability? The roles of big data analytics, green innovation, and organizational identity in gaining green competitive advantage”, *Technology Analysis and Strategic Management*, pp. 1-15, doi: [10.1080/09537325.2023.2293867](https://doi.org/10.1080/09537325.2023.2293867).
- Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J. (2019), “Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and the moderating effect of the environment”, *British Journal of Management*, Vol. 30 No. 2, pp. 272-298, doi: [10.1111/1467-8551.12343](https://doi.org/10.1111/1467-8551.12343).
- Mishra, D., Luo, Z., Hazen, B., Hassini, E. and Foropon, C. (2018), “Organizational capabilities that enable big data and predictive analytics diffusion and organizational performance: a resource-based perspective”, *Management Decision*, Vol. 57 No. 8, pp. 1734-1755, doi: [10.1108/md-03-2018-0324](https://doi.org/10.1108/md-03-2018-0324).
- Muthén, L.K. and Muthén, B.O. (2012), *Mplus-statistical Analysis with Latent Variables: User’s Guide*, 7th ed., Muthén & Muthén, Los Angeles, CA.
- Newbury, W. (2010), “Reputation and supportive behavior: moderating impacts of foreignness, industry and local exposure”, *Corporate Reputation Review*, Vol. 12 No. 4, pp. 388-405, doi: [10.1057/crr.2009.27](https://doi.org/10.1057/crr.2009.27).
- Nizetic, S., Djilali, N., Papadopoulos, A. and Rodrigues, J.J. (2019), “Smart technologies for promotion of energy efficiency, utilization of sustainable resources and waste management”, *Journal of Cleaner Production*, Vol. 231, pp. 565-591, doi: [10.1016/j.jclepro.2019.04.397](https://doi.org/10.1016/j.jclepro.2019.04.397).
- Nunnally, J.C. (1978), *Psychometric Theory*, 2d ed., McGraw-Hill, New York.
- Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y. and Podsakoff, N.P. (2003), “Common method biases in behavioral research: a critical review of the literature and recommended remedies”, *Journal of Applied Psychology*, Vol. 88 No. 5, pp. 879-903, doi: [10.1037/0021-9010.88.5.879](https://doi.org/10.1037/0021-9010.88.5.879).
- Qiu, L., Jie, X., Wang, Y. and Zhao, M. (2020), “Green product innovation, green dynamic capability, and competitive advantage: evidence from Chinese manufacturing enterprises”, *Corporate Social Responsibility and Environmental Management*, Vol. 27 No. 1, pp. 146-165, doi: [10.1002/csr.1780](https://doi.org/10.1002/csr.1780).
- Redman, C.L. (2014), “Should sustainability and resilience be combined or remain distinct pursuits?”, *Ecology and Society*, Vol. 19 No. 2, p. 37, doi: [10.5751/es-06390-190237](https://doi.org/10.5751/es-06390-190237).
- Rezende, L.d. A., Bansi, A.C., Alves, M.F.R. and Galina, S.V.R. (2019), “Take your time: examining when green innovation affects financial performance in multinationals”, *Journal of Cleaner Production*, Vol. 233, pp. 993-1003, doi: [10.1016/j.jclepro.2019.06.135](https://doi.org/10.1016/j.jclepro.2019.06.135).
- Salvadó, J.A., de Castro, G.M., Verde, M.D. and López, J.E.N. (2012), *Environmental Innovation and Firm Performance: A Natural Resource-Based View*, Palgrave Macmillan.
- Saunila, M., Ukko, J. and Rantala, T. (2018), “Sustainability as a driver of green innovation investment and exploitation”, *Journal of Cleaner Production*, Vol. 179, pp. 631-641, doi: [10.1016/j.jclepro.2017.11.211](https://doi.org/10.1016/j.jclepro.2017.11.211).
- Sellitto, M.A. and Hermann, F.F. (2019), “Influence of green practices on organizational competitiveness: a study of the electrical and electronics industry”, *Engineering Management Journal*, Vol. 31 No. 2, pp. 98-112, doi: [10.1080/10429247.2018.1522220](https://doi.org/10.1080/10429247.2018.1522220).

- Sestino, A., Kahlawi, A. and De Mauro, A. (2023), "Decoding the data economy: a literature review of its impact on business, society and digital transformation", *European Journal of Innovation Management*. doi: [10.1108/EJIM-01-2023-0078](https://doi.org/10.1108/EJIM-01-2023-0078).
- Shah, N., Irani, Z. and Sharif, A.M. (2017), "Big data in an HR context: exploring organizational change readiness, employee attitudes and behaviors", *Journal of Business Research*, Vol. 70, pp. 366-378, doi: [10.1016/j.jbusres.2016.08.010](https://doi.org/10.1016/j.jbusres.2016.08.010).
- Shah, T.R., Kautish, P. and Mehmood, K. (2023), "Influence of robots service quality on customers' acceptance in restaurants", *Asia Pacific Journal of Marketing and Logistics*, Vol. 35 No. 12, pp. 3117-3137.
- Shang, Y., Mehmood, K., Iftikhar, Y., Aziz, A., Tao, X. and Shi, L. (2021), "Energizing intention to visit rural destinations: how social media disposition and social media use boost tourism through information publicity", *Frontiers in Psychology*, Vol. 12, 782461, doi: [10.3389/fpsyg.2021.782461](https://doi.org/10.3389/fpsyg.2021.782461).
- Shang, Y., Rehman, H., Mehmood, K., Xu, A., Iftikhar, Y., Wang, Y. and Sharma, R. (2022), "The nexuses between social media marketing activities and consumers' engagement behaviour: a two-wave time-lagged study", *Frontiers in Psychology*, Vol. 13, 811282, doi: [10.3389/fpsyg.2022.811282](https://doi.org/10.3389/fpsyg.2022.811282).
- Shi, J., Zhou, J. and Zhu, Q. (2019), "Barriers of a closed-loop cartridge remanufacturing supply chain for urban waste recovery governance in China", *Journal of Cleaner Production*, Vol. 212, pp. 1544-1553, doi: [10.1016/j.jclepro.2018.12.114](https://doi.org/10.1016/j.jclepro.2018.12.114).
- Shin, S. and Ki, E.-J. (2019), "The effects of congruency of environmental issue and product category and green reputation on consumer responses toward green advertising", *Management Decision*, Vol. 57 No. 3, pp. 606-620, doi: [10.1108/md-01-2017-0043](https://doi.org/10.1108/md-01-2017-0043).
- Soewarno, N., Tjahjadi, B. and Fithrianti, F. (2019), "Green innovation strategy and green innovation: the roles of green organizational identity and environmental organizational legitimacy", *Management Decision*, Vol. 57 No. 11, pp. 3061-3078, doi: [10.1108/md-05-2018-0563](https://doi.org/10.1108/md-05-2018-0563).
- Song, W. and Yu, H. (2018), "Green innovation strategy and green innovation: the roles of green creativity and green organizational identity", *Corporate Social Responsibility and Environmental Management*, Vol. 25 No. 2, pp. 135-150, doi: [10.1002/csr.1445](https://doi.org/10.1002/csr.1445).
- Su, X., Zeng, W., Zheng, M., Jiang, X., Lin, W. and Xu, A. (2022), "Big data analytics capabilities and organizational performance: the mediating effect of dual innovations", *European Journal of Innovation Management*, Vol. 25 No. 4, pp. 1142-1160, doi: [10.1108/ejim-10-2020-0431](https://doi.org/10.1108/ejim-10-2020-0431).
- Sun, B. and Liu, Y. (2021), "Business model designs, big data analytics capabilities and new product development performance: evidence from China", *European Journal of Innovation Management*, Vol. 24 No. 4, pp. 1162-1183, doi: [10.1108/ejim-01-2020-0004](https://doi.org/10.1108/ejim-01-2020-0004).
- Tang, A.K., Lai, K.H. and Cheng, T. (2012), "Environmental governance of enterprises and their economic upshot through corporate reputation and customer satisfaction", *Business Strategy and the Environment*, Vol. 21 No. 6, pp. 401-411, doi: [10.1002/bse.1733](https://doi.org/10.1002/bse.1733).
- Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H. and Sui, F. (2018), "Digital twin-driven product design, manufacturing and service with big data", *International Journal of Advanced Manufacturing Technology*, Vol. 94 Nos 9-12, pp. 3563-3576, doi: [10.1007/s00170-017-0233-1](https://doi.org/10.1007/s00170-017-0233-1).
- Tseng, M.L., Tan, R.R., Chiu, A.S., Chien, C.F. and Kuo, T.C. (2018), "Circular economy meets industry 4.0: can big data drive industrial symbiosis?", *Resources Conservation and Recycling*, Vol. 131, pp. 146-147, doi: [10.1016/j.resconrec.2017.12.028](https://doi.org/10.1016/j.resconrec.2017.12.028).
- Ullah, F., Wu, Y., Mehmood, K., Jabeen, F., Iftikhar, Y., Acevedo-Duque, Á. and Kwan, H.K. (2021), "Impact of spectators' perceptions of corporate social responsibility on regional attachment in sports: three-wave indirect effects of spectators' pride and team identification", *Sustainability*, Vol. 13 No. 2, p. 597, doi: [10.3390/su13020597](https://doi.org/10.3390/su13020597).
- Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.F., Dubey, R. and Childe, S.J. (2017), "Big data analytics and firm performance: effects of dynamic capabilities", *Journal of Business Research*, Vol. 70, pp. 356-365.

-
- Waqas, M., Honggang, X., Ahmad, N., Khan, S.A.R. and Iqbal, M. (2021), "Big data analytics as a roadmap towards green innovation, competitive advantage and environmental performance", *Journal of Cleaner Production*, Vol. 323, 128998, doi: [10.1016/j.jclepro.2021.128998](https://doi.org/10.1016/j.jclepro.2021.128998).
- Xia, H., Vu, H.Q., Law, R. and Li, G. (2020), "Evaluation of hotel brand competitiveness based on hotel features ratings", *International Journal of Hospitality Management*, Vol. 86, 102366, doi: [10.1016/j.ijhm.2019.102366](https://doi.org/10.1016/j.ijhm.2019.102366).
- Yadav, G., Seth, D. and Desai, T.N. (2017), "Analysis of research trends and constructs in context to lean six sigma frameworks", *Journal of Manufacturing Technology and Management*, Vol. 28 No. 6, pp. 794-821, doi: [10.1108/jmtm-03-2017-0043](https://doi.org/10.1108/jmtm-03-2017-0043).
- Yu, X., Mehmood, K., Paulsen, N., Ma, Z. and Kwan, H.K. (2021), "Why safety knowledge cannot be transferred directly to expected safety outcomes in construction workers: the moderating effect of physiological perceived control and mediating effect of safety behavior", *Journal of Construction Engineering and Management*, Vol. 147 No. 1, 04020152, doi: [10.1061/\(asce\)co.1943-7862.0001965](https://doi.org/10.1061/(asce)co.1943-7862.0001965).
- Zameer, H., Wang, Y., Yasmeen, H. and Mubarak, S. (2020), "Green innovation as a mediator in the impact of business analytics and environmental orientation on green competitive advantage", *Management Decision*, Vol. 60 No. 2, pp. 488-507, doi: [10.1108/md-01-2020-0065](https://doi.org/10.1108/md-01-2020-0065).
- Zhan, Y., Tan, K.H., Li, Y. and Tse, Y.K. (2018), "Unlocking the power of big data in new product development", *Annals of Operations Research*, Vol. 270 Nos 1-2, pp. 577-595, doi: [10.1007/s10479-016-2379-x](https://doi.org/10.1007/s10479-016-2379-x).
- Zhu, Q. and Sarkis, J. (2006), "An inter-sectoral comparison of green supply chain management in China: drivers and practices", *Journal of Cleaner Production*, Vol. 14 No. 5, pp. 472-486, doi: [10.1016/j.jclepro.2005.01.003](https://doi.org/10.1016/j.jclepro.2005.01.003).

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