Contribution of big data analytics to developing sustainable products

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Abstract

Big data has become a thrilling milestone for gaining new opportunities and improving performance. Recent research indicated that big data analytics—the fourth paradigm of science—has the potential to develop business practices and sustainable operations; yet, concerning its contribution to developing sustainable products, there is a notable lack of knowledge and uncertainty. Thus, this study aims to investigate the contribution of big data analytics to developing sustainable products; the products that benefit the triple bottom line, i.e., economy, environment, and society. As such, the method of the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution is employed. The findings revealed that big data analytics could make a considerable contribution to developing the efficiency of product end-of-life management, among other product sustainability criteria identified. Such an appraisal, which is of critical importance to sustainable development, can be beneficial to decision makers and those who are keen to gain a better knowledge of big data analytics and its contribution to developing sustainable products.

Keywords
Big data analytics, Industry 4.0 technologies, Sustainable products development, Sustainable product criteria, Manufacturing sustainability

1. Introduction
Big data has been viewed as a large volume of scientific data for visualization (Cox and Ellsworth 1997). According to Laney (2001), it is characterized by the 3Vs, i.e., Volume, Variety, and Velocity; however, there may be other characteristics needing to be considered (Ren et al. 2019), e.g., Value (Gantz et al. 2011), and/or Veracity referring to the unreliability and uncertainty inherent in some sources of data (Zikopoulos et al. 2012). Big Data Analytics (BDA) is hence regarded as the "next big thing" in managerial and developmental initiatives and/or in nurturing business opportunities (Kwon et al. 2014; Ali et al. 2020). It refers to vast and intricate data sets and analytical methods in applications that need the deployment of complex and unique technology for archiving, managing, analyzing, and visualizing. BDA's significant impact will be witnessed within the manufacturing context, specifically in R&D, production, customer service, maintenance/repair, and overhaul technical support, as well as recycling and remanufacturing. By providing insight into manufacturers, it enables them to understand their current and projected situations, and at the same time identify the requirements for achieving more optimal outcomes. It has the potential to drive the adoption of cleaner production methods and facilitate the progress of sustainable production and consumption practices (Zhang et al. 2017). Consequently, practitioners can enhance the value of various products through the utilization of this concept (Wang et al. 2021; Gholami et al. 2022).

Recent research indicated that BDA has also the potential to develop sustainable products. In this regard, Ali et al. (2020) indicated the positive impact of big data analytics on sustainable product development is evident, and this development, in turn, significantly influences organizational performance. BDA is shifting the process of sustainable products development (Johnson et al. 2017). In pursuit of sustainability, organizations are harnessing the power of big data by collecting valuable information to facilitate the process of sustainable product development (Tan and Zhan 2017). Taking into account the environmental aspect, sustainable products can be designed and developed with a focus on minimizing negative environmental impacts through incorporating principles such as resource efficiency, renewable materials, energy conservation, waste reduction, and low emissions (Jawahir et al. 2006; De Silva et al. 2009; Jayal et al. 2010; Shuaib et al. 2014; Letchumanan et al. 2022). Taking into account the social aspect, sustainable products take into account social facets of development by ensuring fair working conditions, respect for human rights, and social inclusion throughout the product lifecycle as well as by improving livelihoods and enhancing the quality of life for communities, especially in developing regions (Gholami et al. 2019; Jamil et al. 2020; Lee et al. 2021). Taking into account the economic aspect, sustainable products are not only environmentally and socially responsible but also economically viable; they can support the transition to a green economy by driving innovation generate economic growth while minimizing negative externalities, offering long-term economic benefits to individuals, businesses, and societies at large (Ren et al. 2019; Joshi et al. 2022; Gholami et al. 2023).

Although anecdotal and theoretical studies have significantly contributed to enriching this research stream, to date, there has been a dearth of empirical evidence regarding the role of BDA in developing sustainable products (Johnson et al. 2017; Tan and Zhan 2017; Ali et al. 2020). Thus, the aim of this study is to investigate the contribution of big data analytics to developing sustainable products. To this end, product sustainability criteria are identified, and the Fuzzy-based Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is employed as a fuzzy modification of TOPSIS to address its limitations in dealing with ambiguity and uncertainty. This method is chosen due to its robust logic and ability to differentiate between criteria of cost and benefit, while also considering solutions that are close to the positive ideal solutions and distant from the anti-ideal solutions.

To highlight the research contribution, this paper is structured as follows: Section 2 provides a review of the literature to offer an understanding of the subject matter; Section 3 details the methods used in the study; Section 4 delves into the analysis and results of the study's objective; and finally, Section 5 presents the conclusions.

2. Literature Review

Based on the 5Vs theory, the process of exploring extensive and diverse data sets in BDA aims to reveal concealed patterns, unidentified correlations, market trends, customer preferences, and other valuable information. This wealth of insights assists organizations in making well-informed business decisions, thereby enhancing sustainability performance and propelling society toward the circular economy (Ren et al. 2019). The capacity of BDA to offer valuable patterns and knowledge for exploring potential markets, enhancing sustainable operational efficiency, and ultimately fostering the development of sustainable products has garnered attention from both industry and academia (Ali et al. 2020; Gholami et al. 2021).

From the perspective of illustrative examples, Siemens utilizes BDA to study operational behaviors by extracting insights from 100,000 measurements obtained from power plants worldwide, hence enabling the implementation of remote diagnostic services (Siemens 2014). Likewise, Ramco Cements Limited, an Indian manufacturing industry leader, leveraged BDA to make savvy business judgments on the development of products and management decisions in the logistics context (Dutta and Bose 2015). Analyzing big data derived from customer feedback, The SPEC, a prominent eyeglasses manufacturer in China, effectively utilized useful insights to generate innovative ideas for new product development (Tan et al. 2015). A specialized turbo machinery manufacturer in China (Shaanxi Blower Group), implemented a product health management center to improve their service quality by utilizing sensor-collected lifecycle big data (Zhang et al. 2017). By employing Boeing's AHMS, real-time big data of in-air airplane operations are gathered and analyzed to proactively alert ground crews about potential maintenance issues prior to landing (Boeing 2017). BDA was employed by the Taiwanese light-emitting diode industry and a Chinese manufacturer of sanitary appliances to better understand the critical features of SCRU and boost their GSCM competence, both of which contributed to greater sustainability in the supply chain (Zhao et al. 2017).

Going through the influential research relating to BDA for sustainable products, Tao et al. (2018) initiated a method for product design, manufacturing, and service driven by digital twins, exploring its application methods, frameworks, and future potential through three illustrative cases. El-Kassar and Singh (2019) developed and test a model demonstrating the relationships among green innovation, its drivers, and factors influencing performance and competitive advantage. Zhang et al. (2017) proposed an overall architecture of BDA for the product lifecycle. Nagy et al. (2018) examined how businesses understand and apply the concept of Industry 4.0 and its tools including IoT, BDA, etc. Haseeb et al. (2019) identified and examined elements of Industry 4.0 including BDA, IoT, etc. to develop sustainable business performance. Bonilla et al. (2018) examined and discussed the sustainability impact and challenges of Industry 4.0 and its related technologies including BDA, IoT, etc. from four dissimilar scenarios. Ren et al. (2019) presented an extensive analysis of BDA in smart manufacturing and propose a product lifecycle-based framework. Diamantoulakis et al. (2015) shed light on the challenges and problems related to BDA encountered by the dynamic energy management employed in smart grid networks and offer an overview of the prevalent data processing techniques and a potential avenue. Bag et al. (2020) assessed the significance of BDA capability for enhancing sustainable supply chain performance using the dynamic capability theory. Kristoffersen et al. (2020) presented the smart circular economy framework, which helps manufacturers achieve SD by translating circular strategies into the business analysis requirements of digital technologies including BDA, IoT, etc. To summarize, there is a growing body of literature that highlights the rising interest in leveraging BDA to extract valuable knowledge, which, in turn, facilitates the development of sustainable products in various industries.

Sustainable products promote the triple bottom line (TBL) by benefiting the environment, society, and economy while ensuring public health, well-being, and environmental preservation throughout their lifespan (Shuaib et al. 2014). Adopting a holistic approach is imperative in the development of sustainable products, ensuring the inclusion of essential criteria from the TBL perspective. This necessitates having a holistic view from the premanufacturing, manufacturing, use, and post-use stages of the product's life cycle to this end (Ahmad et al. 2018; Gholami et al. 2022). Numerous notable initiatives have been undertaken to enhance the sustainability performance of products, with several primary studies uncovering the key indicators that influence sustainable product development (Jawahir et al. 2006; De Silva et al. 2009; Jayal et al. 2010; Haapala et al. 2013; Shuaib et al. 2014). As a whole, this progress has been mapped out through the clustering, evaluation, and enhancement of interconnected indicators (Shuaib et al. 2014). Among the various influential indicators, eleven key indications, depicted in Figure 1, have been primarily considered (Gholami et al. 2022). These encompass eleven distinct criteria, each identified by a unique code and name. The economic aspect includes initial investment, direct/indirect costs, and losses, all of which have a desired level of minimum. The environmental aspect includes material use, energy use, waste and emissions, and product end-of-life management efficiency, all of which have a desired level of minimum except for product end-of-life management efficiency, which has a desired level of maximum. Lastly, the social aspect includes product quality and durability, functional performance, safety and health impact, and regulations and certifications effectiveness, all of which have a desired level of maximum. These indicators, alongside the TBL, overtly incorporate the 6Rs (reduce, reuse, recover, redesign, remanufacture, and recycle) to facilitate sustainable production. They serve as attributes or variables that indicate the behavior or state of a system and require a metric for comparing against a baseline or sustainable benchmark. Nonetheless, going through the literature indicates that there has been no research conducted to analyze the extent of BDA's contribution to the development of sustainable products based on the mentioned criteria.

Cr1: Initial Investment (e.g., capital costs), **Cr2:** Direct/Indirect Costs (e.g., labor/legal costs), **Cr3:** Losses (e.g., quality losses), **Cr4:** Material Use (e.g., material utilization), **Cr5:** Energy Use (e.g., energy from renewable and non-renewable sources), **Cr6:** Waste and Emissions (e.g., solid/liquid waste and gaseous emissions), **Cr7:** Product End-of-Life Management efficiency (e.g., EoL product reuse/recovery), **Cr8:** Product Quality and Durability (e.g., product reliability and maintenance), **Cr9:** Functional Performance (e.g., product customizability), **Cr10:** Safety and Health Impact (e.g., product safety), **Cr11:** Regulations and Certifications Effectiveness (e.g., product EoL certification).

Figure 1. Principal criteria affecting sustainable product development

3. Methods

The dominant decision-making method utilized is TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), originally introduced by Hwang and Yoon (1981) as a method to assess the alternatives' performance based on their similarity to the ideal solution. Based on the theory underlying TOPSIS, the principle is to select an alternative that has the shortest distance from the positive ideal solution (PIS) and the longest distance from the negative ideal solution (NIS) when addressing a MCDM problem (Chen 2000). With its straightforward computation process, systematic procedure, and logical representation of human choice, TOPSIS eliminates the need for pair-wise comparisons generally adopted by methods like the AHP (Shen et al. 2013; Koyuncu et al. 2021; Gholami et al. 2022). A classical TOPSIS and a centroid-based FTOPSIS technique could not represent the preferences of decision makers, but employing an integral-based FTOPSIS might change the ranking of the evaluations. Correspondingly, regarding the knowledge management (KM) of experts, the FTOPSIS method was utilized to select and prioritize the KM strategies while the maturity level was taken into consideration. In this paper, the FTOPSIS method is employed due to the challenges of TOPSIS method in quantifying numerous decision criteria and the need to incorporate judgments expressed in numerical terms with linguistic values. Based on the nature of the problem, the FTOPSIS method offers the capability to evaluate and make decisions by providing both numerical and verbal expressions in a comprehensive manner (Chen 2000).

Due to the subjective, uncertain, and ambiguous nature of human judgments and preferences, exact numerical values are often insufficient for modeling real-life situations under various conditions. To address the uncertainties and ambiguities inherent in human cognition and reasoning, Zadeh (1965) introduced fuzzy set theory as a mathematical framework for processing data. It offers the capability to handle vagueness by allowing partial set membership instead of crisp set membership, thereby providing mathematical tools to tackle such uncertainties. In this paper, the utilization of triangular fuzzy numbers for preference assessment is based on their ease of use and calculation, facilitating decision-makers in their evaluation process. A triangular fuzzy number is indicated as (a, b, c) where a ≤ b ≤ c, encompasses the parameters a, b, and c, representing the smallest possible value, the most promising value, and the largest possible value, respectively. Let X represent a collection of objects defined as the universe, and let x represent its constituents. A membership function $f_A(x)$ demonstrates a fuzzy subset A in X and each element x in A is connected with a real integer between 0 and 1. As seen in Figure 2, a fuzzy set is defined by its membership function as follows:

$$f_A(x) = \begin{cases} \frac{x-a}{b-a} & x < a, x < c, a \le x \le b \\ \\ \frac{c-x}{c-b} & b \le x \le c \end{cases} \tag{1}$$

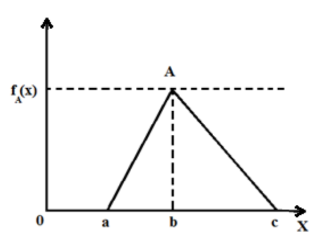

Figure 2. Membership function of triangular fuzzy number A

The following are a few fundamental definitions of fuzzy concepts that are utilized in the proposed fuzzy TOPSIS approach (Zadeh 1965). Consider A = (a, b, c) while B = (a_1, b_1, c_1) to be two triangular fuzzy numbers. Therefore, the basic operations of triangular fuzzy numbers are expressed as follows:

$$A(+)B = (a, b, c)(+)(a_1, b_1, c_1) = (a + a_1, b + b_1, c + c_1) \tag{2}$$

$$A(-)B = (a, b, c)(-)(a_1, b_1, c_1) = (a - a_1, b - b_1, c - c_1) \tag{3}$$

$$KA = (ka, kb, kc) \tag{4}$$

$$(A)^{-1} = \left(\frac{1}{a}, \frac{1}{b}, \frac{1}{c}\right) \tag{5}$$

To calculate the distance between fuzzy numbers A and B, the equation below is used:

$$d(A,B) = \sqrt{\frac{1}{3}[(a-a_1)^2 + (b-b_1)^2 + (c-c_1)^2} \tag{6}$$

With the assumption of K decision makers in a decision group, the fuzzy rating of each decision maker Dk (k = 1, 2, 3, 4, …, K) can be represented as a positive triangular fuzzy number Rk (k = 1, 2, 3, 4, …, K) with membership function FRK (x). The aggregated fuzzy rating can therefore be characterized as:

$$R = (a,b,c) \qquad k = 1,2,3,4,\ldots,K \tag{7}$$

Where $a = min_k\{a_k\}$, $b = 1/k\ \sum_{k=1}^{k} b_k$, and c= $max_k\{c_k\}$

Following the establishment of the decision group, the next step involves the selection of verbal variables used for evaluating the alternatives and determining the significance weights of the criteria. Subsequently, decision makers assess the alternatives and criteria utilizing these chosen verbal variables. Outlined below are the logical and straightforward steps of the implementation process in FTOPSIS (Hwang and Yoon 1981; Chen et al. 2006; Shen et al. 2013).

Step 1: The fuzzy-decision matrix which has been normalized is defined as:

$R = [r_{ij}]_{m.n}$

where B indicates the benefit criteria and C indicates the cost criteria

$$r_{ij} = \left(\frac{a_{ij}}{c_j}, \frac{b_{ij}}{c_j}, \frac{c_{ij}}{c_j}\right) \ , j \in B \tag{8}$$

$c_j \ = max_i\ c_{ij}, j \in B$

$$r_{ij} = \left(\frac{a_j^{\ -}}{c_{ij}}, \frac{a_j^{\ -}}{b_{ij}}, \frac{a_j^{\ -}}{c_j a_{ij}}\right) \tag{9}$$

$a_j^{\ -} = min_i\ \mathrm{a}_{ij}, j \in C$

Step 2: By multiplying the weights of the criteria to the normalized matrix, the weighted normalized decision matrix v_{ij} can be obtained:

$$V = [v_{ij}]mn \qquad i = 1,2,3,4,\ldots,m\,; j = 1,2,3,4,\ldots,n \tag{10}$$

where $v_{ij} = r_{ij} \cdot w_j$ and w_j represents the weight of the jth attribute or criterion.

Step 3: Equations below are used to calculate the positive-ideal solution (PIS, A*) and negative-ideal solution (NIS, A−):

$$A^* = (v_1^*, v_2^*, \ldots, v_n^*) \tag{11}$$

$$A^- = (v_1^-, v_2^-, \ldots, v_n^-) \tag{12}$$

where v_j^* = maxi { $v$ija } and v_j^- = mini{ $v$ija }, i = 1, 2, 3, 4, …, m, j = 1, 2, 3, 4, …, n.

Step 4: The distance between PIS and NIS for each alternative is computed as below:

$$d_i^* = \sum_{j=1}^{n} d_v(v_{ij}, v_j^*)\,, \qquad i = 1,2,3,4,\ldots,m \tag{13}$$

$$d_i^- = \sum_{j=1}^{n} d_v(v_{ij}, v_j^-)\,, \qquad i = 1,2,3,4,\ldots,m \tag{14}$$

Step 5: Equation below is used to calculate the closeness coefficient (CCi) of each alternative:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^*} \qquad i = 1,2,3,4,\ldots,m \tag{15}$$

Step 6: By comparing the CCi values at the end of the analysis, the ranking for all alternatives can be identified. Alternative Ai is closer to the FPIS (A*) and farther from FNIS (A−) as CC1 approaches to 1. By arranging the alternatives in descending order of CC1, the ranking order of all alternatives is determined.

4. Results and Discussion

The employed research methods effectively fulfill the research purpose, shedding light on various implications for decision-makers seeking to understand the potential contribution of BDA in developing sustainable products within the automotive manufacturing context. These considerations arise from the mounting pressure on automotive industries in recent decades to enhance their sustainability performance, driven by concerns over environmentally and socially harmful products and practices (Lee et al. 2023). Notably, the adoption of sustainability standards in the development of automotive products remains rare, as highlighted by Ahmad et al. (2018) and Ali et al. (2020).

After establishing product sustainability criteria (see Figure 1), the decision-making team is made to further evaluation. The linguistic variables are accordingly applied (Chen et al. 2000; Koyuncu et al. 2021; Gholami et al. 2022); where very low (VL), low (L), medium-low (ML), medium (M), medium-high (MH), high (H), very high (VH) represent the fuzzy numbers (0,0,0.1), (0,0.1,0.3), (0.1,0.3,0.5), (0.3,0.5,0.7), (0.5,0.7,0.9), (0.7,0.9,1.0), (0.9,1.0,1.0) respectively for the relative importance weights of eleven criteria as well as very poor (VP), poor (P), medium poor (MP), fair (F), medium good (MG), good (G), very good (VG) represent the fuzzy numbers (0,0,1), (0,1,3), (1,3,5), (3,5,7), (5,7,9), (7,9,10), (9,10,10) for the ratings. The fuzzy numbers represent the degree of membership of the variable in its corresponding fuzzy set; a set of values that have some degree of membership, rather than a precise value (Zadeh, 1965). The fuzzy numbers in this study are represented using three values in parentheses: the lower bound–the minimum degree of membership for the variable, modal value–the highest degree of membership for the variable, and upper bound–the maximum degree of membership for the variable. These values represent the degree of membership of the corresponding linguistic variable in its fuzzy set. According to the linguistic variables applied, the decision makers evaluate the importance of the criteria and the contributory ratings of BDA to the criteria.

Table 1 displays the appraisal information contributed by the decision-making group, where aggregated fuzzy numbers are derived by averaging the group's fuzzy judgments. The fuzzy-decision matrix lists various criteria (Cr1 through Cr11) and their respective importance weights. The importance weights are represented as aggregated fuzzy weights, which are numerical values that indicate the degree of importance assigned to each criterion. The fuzzy weights are represented as three values within parentheses, which correspond to low, medium, and high importance, respectively. The importance of different criteria related to BDA, their normalized fuzzy weights, and their closeness coefficient (CC) indicating the contributory ratings of BDA to the overall set of criteria are also demonstrated in the table. The CC value is represented as a numerical value between 0 and 1, with higher values indicating greater contribution.

As a whole, the analyses and outcomes indicate that Cr7, representing product end-of-life management efficiency (Figure 1), boasts the highest closeness coefficient of 0.79. It is followed by Cr8 and Cr9 with coefficients of 0.58 and 0.52, respectively. Consequently, the ranking of BDA's contribution to each indicator, which signifies a higher rank for a greater perceived level of contribution, highlights the significant potential of BDA in advancing product end-of-life management efficiency. The examination and evaluation of such aspects hold significant value in the realm of sustainable development, providing invaluable insights for decision-makers and policymakers seeking an understanding of the role of big data analytics in the development of sustainable products. This analysis serves as a valuable resource for those striving to make informed decisions and formulate effective policies that align with the principles of sustainability. By delving into the intricacies of big data analytics and its impact on the creation of sustainable products, this assessment empowers stakeholders with the knowledge and perspective necessary to navigate the complex landscape of sustainable product development.

Table 1. Fuzzy-decision matrix weighted and normalized

Criteria	Criteria importance	BDA importance normalized fuzzy weights and contribution to the criteria		
	Aggregated fuzzy weight	Aggregation	Normalized fuzzy weight	CC
Cr1	(0.83,0.96,1.00)	(2.33, 4.33, 6.33)	(0.04, 0.06, 0.14)	0.09
Cr2	(0.83,0.96,1.00)	(0.33, 1.66, 3.66)	(0.07, 0.18, 1.00)	0.44
Cr3	(0.83,0.96,1.00)	(0.66, 2.33, 4.33)	(0.05, 0.13, 0.50)	0.27
Cr4	(0.83,0.96,1.00)	(3.66, 5.66, 7.66)	(0.03, 0.05, 0.09)	0.06
Cr5	(0.56,0.76,0.93)	(3.66, 5.66, 7.66)	(0.02, 0.04, 0.08)	0.05
Cr6	(0.76,0.93,1.00)	(0.33, 1.66, 3.66)	(0.07, 0.17, 1.00)	0.45
Cr7	(0.76,0.93,1.00)	(9.00,10.0,10.00)	(0.60, 0.90, 1.00)	0.79
Cr8	(0.83,0.96,1.00)	(4.33, 6.33, 8.33)	(0.35, 0.60, 0.83)	0.58
Cr9	(0.83,0.96,1.00)	(3.66, 5.66, 7.66)	(0.29, 0.53, 0.76)	0.52
Cr10	(0.63,0.83,0.96)	(1.00, 3.00, 5.00)	(0.06, 0.24, 0.48)	0.29
Cr11	(0.63,0.83,0.96)	(0.33, 1.66, 3.66)	(0.02, 0.13, 0.34)	0.20

5. Conclusion

Big data analytics is experiencing rapid global growth as organizations pursue maximum value and sustainable competitive advantage. However, when it comes to its role in developing sustainable products, there is a lack of knowledge and certainty, which calls for innovative research. As such, this study is aimed at investigating the potential contribution of BDA to the development of sustainable products. To this end, a Fuzzy TOPSIS approach is employed to analyze the subject based on a set of respective criteria. The analyses and findings demonstrated that the criterion 'product end-of-life management efficiency' has the highest closeness coefficient of 0.79, revealing that BDA could make a considerable contribution to developing product end-of-life management efficiency, among other product sustainability criteria identified. The findings would significantly contribute to the body of BDA knowledge as this study stands as the primary empirical investigation exploring the contribution of BDA in the development of sustainable products on the basis of product sustainability criterion. The significance of this research lies in its ability to bridge the gap between data-driven insights and sustainable practices, ultimately paving the way for a more sustainable future. The enriched insights provided by this study may open up new possibilities and avenues for further exploration and innovation in the field of BDA for sustainable products. Further studies are recommended to extensively investigate and delve deeper into the findings, and to also explore a broader range of criteria that have the potential to influence the development of sustainable products within the realm of BDA. The vastness and complexity of this research domain call for continuous exploration and scholarly inquiry to unlock new insights and push the boundaries of knowledge in this field. It is imperative to expand our understanding and uncover hidden dimensions to fully grasp the transformative potential of BDA in fostering sustainable products development, which is of vital importance to sustainable development.

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