sustainability

Article

Big Data Analytics for Sustainable Products: A State-of-the-Art Review and Analysis

Hamed Gholami [1,*], Jocelyn Ke Yin Lee [1] and Ahad Ali [2]

[1] Mines Saint-Etienne, Université Clermont Auvergne, INP Clermont Auvergne, CNRS, UMR 6158 LIMOS, F-42023 Saint-Etienne, France; ke.lee@emse.fr or jocelyn.leekeyin@gmail.com
[2] A. Leon Linton Department of Mechanical, Robotics and Industrial Engineering, Lawrence Technological University, Southfield, MI 48075, USA; sali@ltu.edu
* Correspondence: hamed.gholami@emse.fr or hamedgholami10@gmail.com

Abstract: Big data analytics, described as the fourth paradigm of science breaking through Industry 4.0 technological development, continues to expand globally as organizations strive to attain the utmost value and sustainable competitive edge. Yet, concerning its contribution to developing sustainable products, there is a need for innovative research due to limited knowledge and uncertainty. This research is hence aimed at addressing (a) how research on big data analytics for sustainable products has evolved in recent years, and (b) how and in what terms it can contribute to developing sustainable products. To do so, this study includes a bibliometric review performed to shed light on the phenomenon gaining prominence. Next, the fuzzy technique for order of preference by similarity to ideal solution, along with a survey, is used to analyze the matter in terms of the respective indicator set. The review's findings revealed that there has been growing global research interest in the topic in the literature since its inception, and by advancing knowledge in the area, progress toward sustainable development goals 7, 8, 9, 12, and 17 can be made. The fuzzy-based analytical findings demonstrated that 'product end-of-life management efficiency' has the highest contributory coefficient of 0.787, followed by 'product quality and durability' and 'functional performance', with coefficients of 0.579 and 0.523, respectively. Such research, which is crucial for sustainable development, offers valuable insights to stakeholders seeking a deeper understanding of big data analytics and its contribution to developing sustainable products.

Keywords: big data analytics; sustainable products; sustainable development goals; manufacturing sustainability indicator set; bibliometric review; empirical analysis; tableau

Citation: Gholami, H.; Lee, J.K.Y.; Ali, A. Big Data Analytics for Sustainable Products: A State-of-the-Art Review and Analysis. *Sustainability* **2023**, *15*, 12758. https://doi.org/10.3390/su151712758

Academic Editors: Tzu-An Chiang and Zhen-Hua Che

Received: 4 August 2023
Revised: 16 August 2023
Accepted: 16 August 2023
Published: 23 August 2023

1. Introduction

Given the growing global interest in sustainable development (SD), delineated as "Our Common Future" in the Brundtland report [1], numerous scientific communities have vigorously engaged in integrating this philosophy into the realm of production to develop sustainable products (sus-products); the products benefiting businesses, individuals, societies and the environment at large. It was further highlighted at the Rio de Janeiro Earth Summit that production sectors hold crucial roles in shaping our common future, underscoring the significance of such sectors [2]. Building on the SD philosophy, the aim of developing sus-products is to fulfill current requirements while ensuring the capacity of future generations to fulfill their own needs. However, to reach a more sustainable state in terms of products, having an all-inclusive view across the total product life-cycle—from preproduction, production, and use through to post-use stages—is necessary [3].

Recognizing science and technology's indispensable role in fostering sustainable development, there is an increasing acknowledgment of the need for the capacity to mobilize and utilize them effectively [4]. Attributable to the unprecedented growth in new data generated by public institutions and industries, the "age of data" is thriving at the present time [5]. Due to its transformative potential in revolutionizing business processes and enhancing performance, the concept of big data has garnered significant admiration from both practitioners and research scholars [6,7]. The persistent global growth of big data analytics (BDA), recognized as a "breakthrough technological development" [8] and "the fourth paradigm of science" [9], can be attributed to organizations' pursuit of attaining sustainable competitive advantage and extracting maximum value [5,10]. Based on the report produced by Forbes, a significant percentage of enterprises believe that BDA will redefine the competitive landscape of their industries in the near future; thus, if they do not take it into careful consideration, they cannot compete in the market [11].

Recent research has indicated that BDA has great potential to develop sus-products; e.g., Ali et al. [6] demonstrated that the positive effect of BDA on sus-products' development correlates with the significant and positive impact that sus-products' development has on organizational performance. According to Johnson et al. [12], BDA is evolving the process of developing sus-products. To facilitate this process, organizations are leveraging information derived from BDA to achieve objectives such as cost reduction, enhanced consumer product adoption, and accelerated time-to-market [13]. Although anecdotal and theoretical research has greatly enriched this understudied area, there is a scarcity of empirical evidence concerning the contribution of BDA to the development of sus-products [6,12,13]. These considerations thereby bring out the following research questions: (1) how has research on BDA for sus-products evolved in recent years? and (2) how and in what terms might BDA contribute to developing sus-products?

The contribution of this research thus entails addressing the aforesaid queries, and, consequently, enriching the area that could help accomplish SD goals, including G7—affordable and clean energy [14,15], G8—decent work and economic growth [16–19], G9—industry, innovation and infrastructure [14–23], G12—responsible consumption and production [14–17,19,22,23], and G17—partnership for the goals [17,19,21,23]. Furthermore, it may contribute to responding to the following question: "Are digital technologies and information management part of the problem or the solution?", as posed by Dwivedi et al. [24], who have highlighted that the alignment of smart initiatives with SD goals is an underdeveloped research area. Based on Kar and Dwivedi [25], there is a need to move beyond "what the big data represents", to "why it is so". However, there remains a lack of research integrating and systematizing the available knowledge on the topic [6], and particularly research analyzing the matter in terms of product sustainability indicators. To do so, a bibliometric analysis, which is a methodological approach to reviewing the literature evolved in the understudied context [26,27], is carried out alongside the method of the fuzzy technique for order of preference by similarity to ideal solution (Fuzzy-TOPSIS), which is a logically sound method used to differentiate between indicators of cost and benefit and adopt solutions aligning closely with positive ideals, while keeping a distance from anti-ideal solutions [28,29].

These methods are further clarified after Section 2, which presents an overview of key concepts, i.e., in Section 3. To accomplish these research contributions, Sections 4 and 5 discuss the analyses and findings in both a theoretical and empirical manner to address the research questions. Section 6 provides limitations and future research directions. Lastly, Section 7 outlines conclusions and final considerations.

2. An Overview of Key Concepts

2.1. Sustainable Products

Sustainable products (sus-products) play a critical role in accomplishing sustainable development, aiming to balance up environmental, social, and economic—the so-called triple bottom line—needs for the well-being of current and future generations.

Considering their environmental aspect, sus-products can be designed and developed with a focus on minimizing negative environmental impacts by incorporating principles such as resource efficiency, renewable materials, energy conservation, waste reduction, and low emissions [30–33]. By promoting sustainable production and consumption patterns, they help protect ecosystems, conserve natural resources, and mitigate environmental degradation [34–36]. Considering their social aspect, sus-products take into account social facets of development by ensuring fair working conditions, respect for human rights, and social inclusion throughout the product lifecycle [6,37]. They can contribute to improving livelihoods and enhancing the quality of life for communities, especially in developing regions [38–40]. Considering their economic aspect, sus-products are not only environmentally and socially responsible, but also economically viable. They support the transition to a green economy by driving innovation, creating new job opportunities, and fostering sustainable business practices [6,41]. Sus-products can generate economic growth while minimizing negative externalities, offering long-term economic benefits to individuals, businesses, and societies at large [22,42,43].

Sus-products encourage resource efficiency by optimizing the use of materials, energy, and water throughout their life cycle. This approach helps reduce waste generation, conserve resources, and minimize environmental footprints [22,30,32]. Moreover, they may also empower consumers to make environmentally and socially responsible choices. Through eco-labeling, certifications, and transparent information, consumers can identify and support sus-products in the market. Sus-products are likewise regarded as part of a broader systems approach to sustainability; by considering the entire life cycle—from pre-manufacturing, manufacturing, and use through to post-use stages, often necessitating the application of the 6Rs (reduce, recover, reuse, recycle, redesign, and remanufacture)—sus-products promote holistic thinking and foster a circular economy [29].

2.2. Big Data Analytics

Big data has been viewed as a large volume of scientific data for visualization [44]; a massive scale of data, both structured and unstructured, that can be accessed in real-time [45,46]; and vast amounts of data from distinct observations that aid the company in making numerous judgments [47]. According to Laney [48], it is characterized by the 3Vs, i.e., volume, variety, and velocity; however, there may be other characteristics that need to be considered [22], e.g., value [49], and/or veracity, which refers to the unreliability and uncertainty inherent in some sources of data [50].

Big data analytics (BDA) is accordingly regarded as the "next big thing" in managerial and developmental initiatives, and/or in nurturing business opportunities [6,51]. Massive and intricate sets of data, along with the need for sophisticated and distinct technologies and tools to archive, manage, analyze, and visualize them, define the essence of BDA [52]. By providing organizations with insights into their present and projected conditions, BDA enables a better understanding of the essential requirements to achieve more desirable outcomes. The ability to add original value to a range of products is one of the enabling aspects of BDA for practitioners [53].

Within the realm of sustainable production, BDA holds the potential to exert a substantial influence across multiple domains, including R&D, manufacturing, customer service, technical support for maintenance/repair and overhaul, recycling, and remanufacturing. Furthermore, BDA facilitates the deployment of cleaner production practices while advancing sustainable production and consumption in an effective manner [9,16]. By systematically collecting and analyzing diverse data generated throughout the entire product lifecycle, it becomes possible to leverage BDA for the effective provision of guidance in various production activities. Supplementarily, BDA assists managers in addressing operational and decision-making challenges by uncovering new value from the relationship and statistical characteristics inherent in diverse data sources [15,20,54]. One potential future trend in manufacturing enterprises involves leveraging BDA to extract value from lifecycle big data and implementing a sterilization-oriented business strategy throughout the entire product lifecycle. This approach has the potential to generate new added value and bolster sustainability efforts [22,55,56].

3. Methods

3.1. Method of the Review

To address the first research question, this study performs a bibliometric analysis, also known as a scientometric analysis, which is a methodological approach to reviewing large volumes of scientific data, particularly in this field of research. This method has effectively been used since its earliest literary incarnations (i.e., [26,57]), which offered a description of bibliometric research, up until its implementation in relatively recent studies (e.g., [3,27,58]). It involves the systematic analysis of published works such as journal articles, conference papers, etc., using quantitative measures, statistical techniques, and analytical approaches. Thus, this study utilized a bibliometric analysis as such.

To this end, Web of Science and Scopus databases, which are regarded as the foremost indexers of global research content, covering titles and abstracts from numerous esteemed publishers throughout the world including ScienceDirect, Springer, Taylor & Francis, Emerald, Wiley, etc., are widely employed to collect the data in the bibliometric analysis [27,59]. This study used the Scopus database, since it offers a larger coverage of journals and documents as well as citation metrics (e.g., FWCI) compared to Web of Science. This step was taken to ensure that no relevant indexed documents were overlooked when compiling the sample set.

By utilizing Scopus as our research database, we formulated our search strategy and string upon the foundations outlined below: (1) the analysis of all electronic searches was constrained to the time period ending in May 2023 (conducted on 20 May 2023), i.e., (AND PUBYEAR < 2023 OR PUBDATETXT ("January 2023" OR "February 2023" OR "March 2023" OR "April 2023" OR "May 2023") AND (EXCLUDE (PUBYEAR, 2024))); (2) no specific time interval was established for the search, aiming to identify the earliest published document associated with the keyword; (3) given that the discourse on BDA for sus-products is still in its nascent stage, there were no restrictions imposed on document and source types; and (4) the language restriction applied exclusively to publications written in English, i.e., (AND (LIMIT-TO (LANGUAGE, "English"))).

The subsequent step involves uncovering the literature's bibliometric structure pertaining to the topic. Consequently, in accordance with BDA for sus-products, the search string conducted was (TITLE-ABS ("Big Data" OR "Big Data Analytic*")) AND TITLE-ABS ("Sustainab*" AND "Product*"), which resulted in detecting a sum of 870 documents after the screening, as discussed in Section 4. The screening process involved a manual review of the documents, where we read the abstracts and, if necessary, the full texts, to identify and exclude any duplicates and irrelevant documents.

3.2. Method of the Analysis

For conducting a more in-depth analysis of how and in what terms BDA might contribute to developing sustainable products, a survey, elaborated upon in Section 5, was applied following the approach outlined by Forza [60] in conjunction with the fuzzy technique for order of preference by similarity to ideal solution (Fuzzy-TOPSIS), as its suitability is determined to be adequate since it effectively differentiates between cost criteria (favoring lower values for greater contributions) and benefit criteria (favoring higher values for greater contributions). As originally introduced by Hwang and Yoon [61], this technique for solving multi-criteria decision-making (MCDM) problems is grounded in the principle that the chosen alternative should possess the shortest geometric distance from the best solution, known as the positive ideal solution (PIS), while simultaneously maintaining the longest geometric distance from the worst solution, referred to as the negative ideal solution (NIS) [28,62]. Fuzzy-TOPSIS, in contrast to the commonly employed approaches of Fuzzy AHP or Fuzzy ANP for analysis and prioritization, offers a less intricate and time-consuming alternative. Moreover, Fuzzy-TOPSIS eliminates the need for additional pair-wise comparisons, further streamlining the process [29,63,64].

Crafted as a fuzzy extension of TOPSIS, it aims to address the limitations of TOPSIS when dealing with circumstances beyond ambiguity and uncertainty. In numerous scenarios, the utilization of precise data proves insufficient for accurately modeling real-life environments due to the inherent uncertainty and inability to estimate individual preferences and decisions solely through precise numerical values [28,62,64]. By introducing the fuzzy set theory, initially proposed by Zadeh [65], into the decision-making process, uncertainties can be effectively addressed, allowing for membership in a partial set rather than a crisp set. This proves advantageous in handling complex decision scenarios. The pioneering work of Bellman and Zadeh [66] established the application of fuzzy sets in the analysis of decision-making problems, leading to the development of fuzzy-based MCDM methods. A membership function is used to establish a fuzzy set, as shown in Equation (1). In the representation of $f_B(s)$, the fuzzy subset B within the set of items S is defined by real numbers ranging from 0 to 1, with each number corresponding to a specific component represented by s. Considering the convenience it offers to decision-makers, this research hence utilized a triangular fuzzy number set to assess preferences effectively. Denoted as (x, y, z), a triangular fuzzy number represents the minimum conceivable, most likely, and maximum conceivable values, with x, y, and z, respectively indicating these values in ascending order, where x ≤ y ≤ z.

$$f_B(s) = \begin{cases} \frac{s-x}{y-x} & s < x, s < z, x \leq s \leq y \\ \frac{z-s}{z-y} & y \leq s \leq z \end{cases} \quad (1)$$

Provided below are essential definitions of fuzzy concepts employed in Fuzzy-TOPSIS, considering B = (x, y, z) and D = (x_1, y_1, z_1), where B and D are two triangular fuzzy number sets. In practice, this is the description of how triangular fuzzy number sets have been characterized:

$$B(+)D = (x,\ y,\ z)(+)(x_1,\ y_1,\ z_1) = (x + x_1,\ y + y_1,\ z + z_1) \quad (2)$$

$$B(-)D = (x,\ y,\ z)(-)(x_1,\ y_1,\ z_1) = (x - x_1,\ y - y_1,\ z - z_1) \quad (3)$$

$$CB = (cx,\ cy,\ cz) \quad (4)$$

$$(B)^{-1} = \left(\frac{1}{x}, \frac{1}{y}, \frac{1}{z}\right). \quad (5)$$

To calculate the distance between fuzzy numbers B and D, the following equation is used:

$$d(B, D) = \sqrt{\frac{1}{3}[(x - x_1)^2 + (y - y_1)^2 + (z - z_1)^2} \quad (6)$$

To represent the decision making of C decision makers, we utilize the fuzzy rating of each decision maker Dc (where c ranges from 1 to C). Each Dc is represented by a positive triangular fuzzy number Rc, with the membership function FRc(x). The aggregated fuzzy rating is accordingly calculated as follows:

$$R = (x,\ y,\ z)\ c = 1,\ 2,\ 3,\ 4,\ 5, \ldots, C \quad (7)$$

where $x = min_c\{x_c\}$, y = $1/c \sum_{c=1}^{c} b_c$, and $z = max_c\{z_c\}$.

Outlined below are a series of straightforward and logical steps that encapsulate the implementation process of the method, ensuring simplicity and adherence to common sense principles [28,29,61,63]:

Step 1: The fuzzy decision matrix that has been normalized is

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

where B represents the benefit criterion set, while C represents the cost criterion set, and

$$r_{ij} = \left(\frac{x_{ij}}{z_j}, \frac{y_{ij}}{z_j}, \frac{z_{ij}}{z_j}\right), j \in B \quad (8)$$

$$z_j = max_i\, z_{ij}, j \in B$$

$$r_{ij} = \left(\frac{x_j{}^-}{z_{ij}}, \frac{x_j{}^-}{y_{ij}}, \frac{x_j{}^-}{z_j x_{ij}}\right) \quad (9)$$

$$x_j^- = min_i\, x_{ij}, j \in C$$

Step 2: Multiplying the normalized matrix by the criteria's weights yields the weighted normalized decision matrix vij:

$$V = [v_{ij}]mn,\ i = 1,2,3,4,5,\ldots,m;\ j = 1,2,3,4,5\ldots,n \quad (10)$$

where vij = rij. wj, and wj is the weight of the jth criterion or attribute.

Step 3: The computation of both the positive ideal solution (PIS, B*) and the negative ideal solution (NIS, B^-) is performed:

$$B^* = (v_1^*, v_2^*, \ldots, v_n^*) \quad (11)$$

$$B^- = (v_1^-, v_2^-, \ldots, v_n^-) \quad (12)$$

where v_j^* = maximum {$v$ijb} and v_j^- = minimum{v_{ijb}}, i = 1,2,3,4,5,. . .,m, j = 1,2,3,4,5,. . .,n.

Step 4: Each alternative's distance from PIS and NIS is computed:

$$d_i^* = \sum_{j=1}^{n} d_v\left(v_{ij}, v_j^*\right),\ i = 1,2,3,4,5,\ldots,m \quad (13)$$

$$d_i^- = \sum_{j=1}^{n} d_v\left(v_{ij}, v_j^-\right),\ i = 1,2,3,4,5,\ldots,m \quad (14)$$

Step 5: Each alternative's closeness coefficient (CC_i) is computed as follows:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^*}\ i = 1,2,3,4,5,\ldots,m \quad (15)$$

Step 6: Upon completion of the steps, the alternatives are sorted based on their CC_i values. Alternative B_i is positioned closer to the FPIS (B*) and more far apart from FNIS (B^-), since CC_1 approaches 1. This signifies that the studied alternatives are orderly ranked in descending order according to the CC_1 value.

4. Results and Discussion on the Review: Theoretical Contribution and Implications

The review method performed (Section 3.1) contributes to addressing how research on BDA for sus-products has evolved in recent years. Based on our formulated search string and research screening, we found a total of 870 documents published in English over a period of 12 years in different formats (Figure 1) (journal papers (46.67%), conference papers (25.17%), review papers (11.26%), book chapters (7.93%), conference reviews (5.40%), books (1.95%), and others (1.61%)).

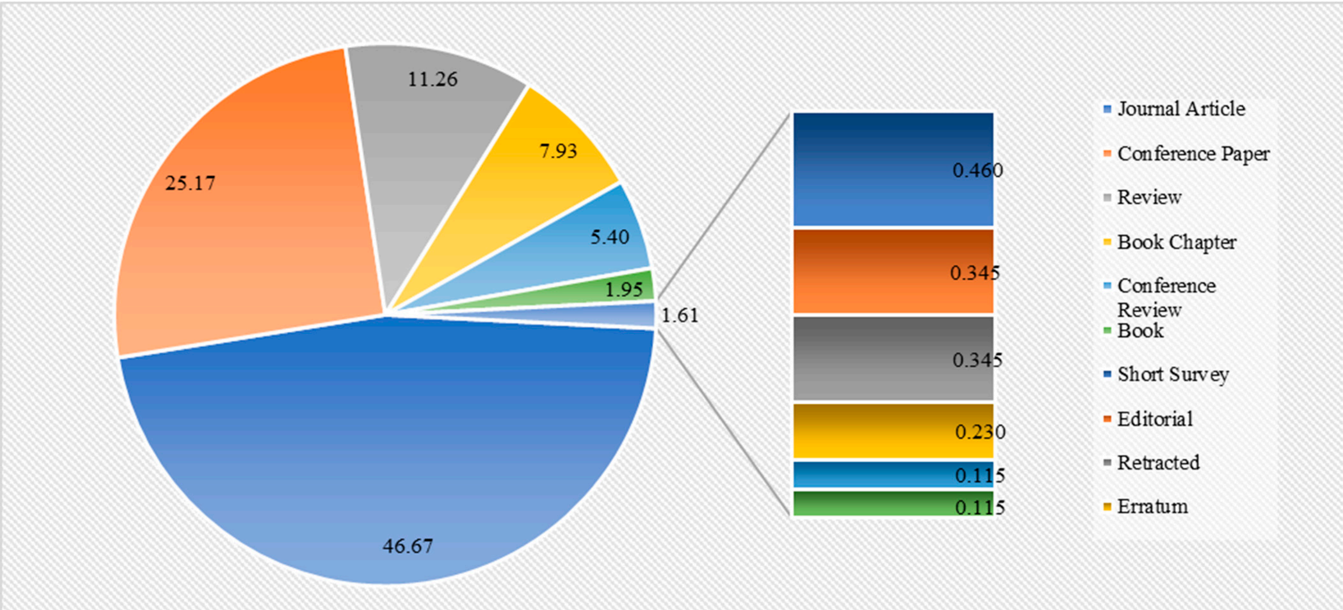
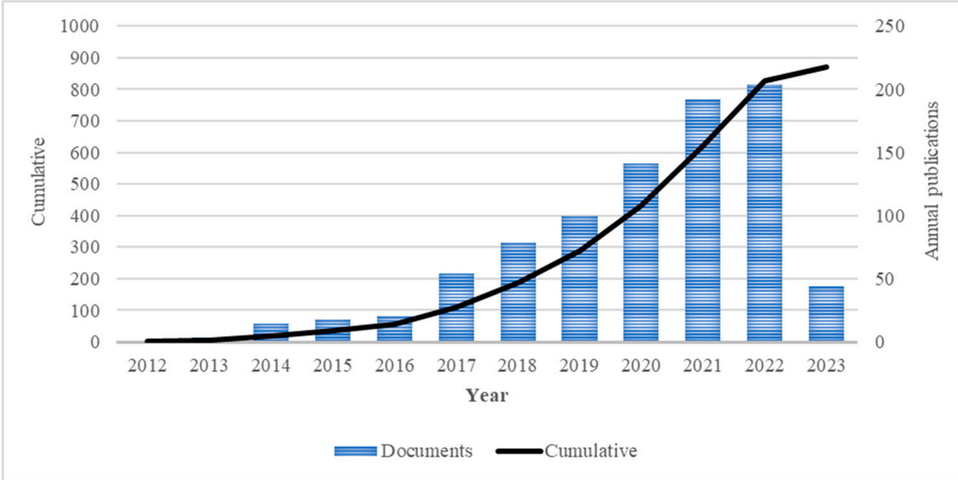


Figure 1. Document types over the years.

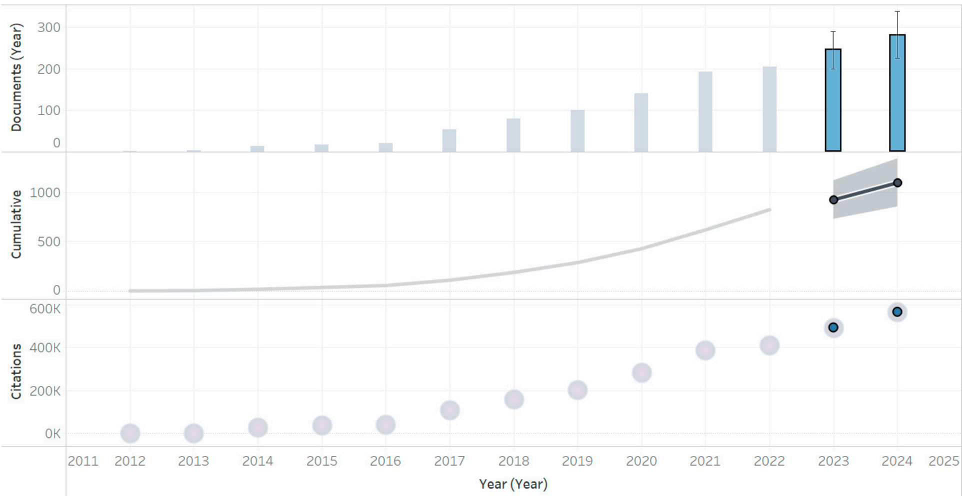
Figure 2a shows the evolution of the topic since its introduction into literary works, i.e., from 2012 to 2023. As recorded by Scopus, the first document was published in 2012 with just a journal paper, i.e., that of Wilson et al. [67]; this study identified the main difficulties and concerns that information system managers face as there is an increasing need for BDA to provide meteorological products in a timely manner. In 2013, a journal paper (i.e., Saguy et al. [68]) and two conference papers under 'IEEE International Conference on Big Data' (Kwac and Rajagopal [69]; Tomic and Fensel [70]) were published. The growth in the number of recorded documents during the initial five-year period did not exhibit a significant trajectory, starting from the aforementioned paper published in 2012 and only reaching 20 documents by 2016. In sum, 56 (6.44%) documents were published, which is roughly similar to the percentage of documents published in 2017 (6.21%), implying that the topic under investigation is novel and in the nascent stages of its development.

Since 2017, the cumulative number of publications and total citations, which are used to acknowledge the relevance of others' works to the discussed topic [27], have experienced a rapid increase due to the substantial growth in annual publications (see Figure 2b). In 2022, the pinnacle of annual publications and citations was observed, with a record-breaking 204 documents and an impressive 412,488 citations. Analogous patterns are discernible in the years 2018, 2019, 2020, and 2021, whereby their annual publications (and citations) experienced incremental surges of 79 (159,422), 100 (201,900), 141 (284,820), and 192 (388,032), respectively, indicating that the cumulative number of publications and the sum of citations have dramatically evolved in recent years.

The observed trends indicate an escalating worldwide research inclination toward the subject topic. In using Tableau 2023.1 software, described as an interactive data visualization software enabling users to analyze and visualize big data in a user-friendly manner, it is even believed that the annual publications will keep growing, as demonstrated in Figure 2b, where the annual total publications (TP), cumulative publications, and total citations (TC) in 2024 are forecasted to increase by 280, 1099, and 566,418, respectively. The evolving diffusion and adoption of an initiative may contribute to this phenomenon; nevertheless, such initiatives are understood as a matter of technological adoption and diffusion, and this adoption–diffusion progression typically streams from leading countries [36,71].



(**a**)



(**b**)

Figure 2. (**a**) Trend in documents published over the years. (**b**) Trend in documents published over the years, with the estimated forecasts.

In using Microsoft Excel 2019 (version 2307) software, Figure 3 maps the involvement of 90 countries in the topic of concern, with the collective contributions of the top five leading countries accounting for 39.35% of the overall publications, including China (TP:196 and TC:5130), the United States (TP:124 and TC:3718), India (TP:90 and TC:1656), the United Kingdom (TP:80 and TC:1965), and Italy (TP:57 and TC:913). The findings are further detailed in Table 1. As seen, China and the US were the topmost countries, owning a significant number of documents, covering 14.1% and 8.92% of the global total publications, respectively. It is also revealed that China, the US, and the UK have collaborated equally with each other on 15 research publications, suggesting that there is an active collaboration between researchers from these countries in various institutions; however, the benefits of such international collaborations not only bring together various perspectives, expertise, and resources from different countries, but also lead to more comprehensive and impactful research outcomes, thus promoting the status of academic institutions.

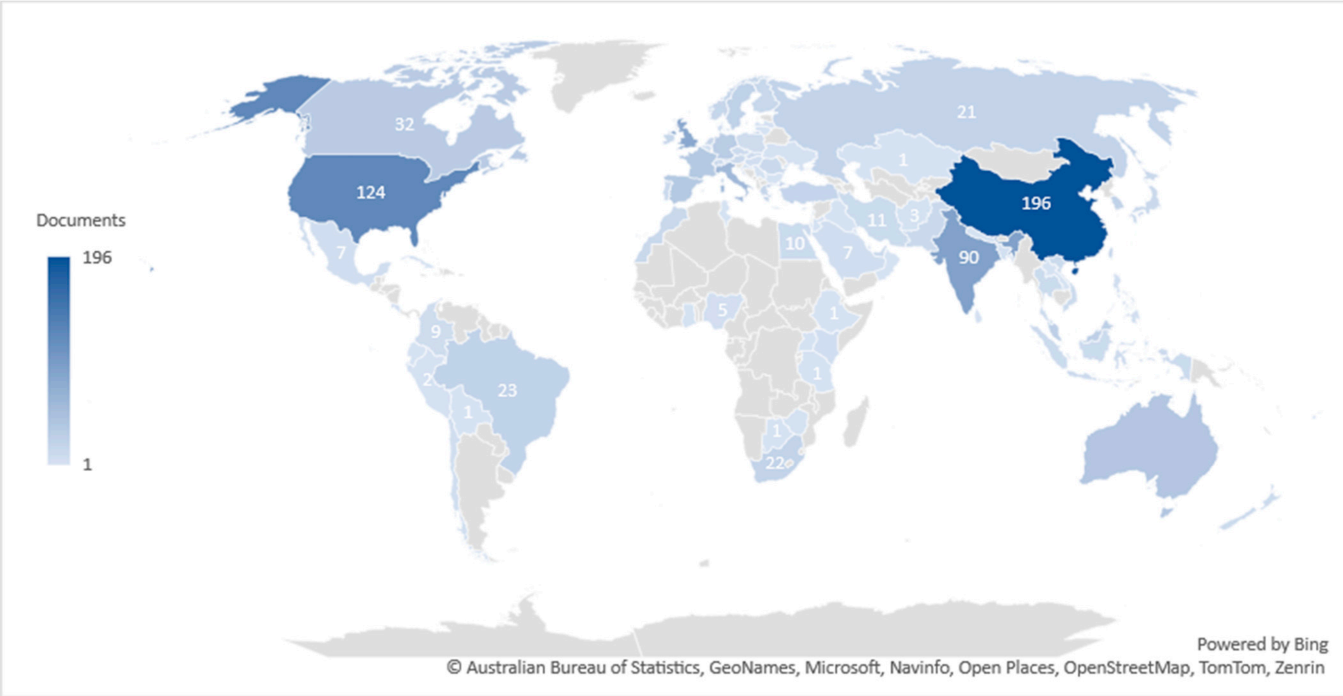


Figure 3. Map of the contributing countries.

Table 1. Top five leading countries.

Country	Publication Year	TP	TC	Document h-Index	Most Collaborative Country (#doc)	Most Productive Institute (#doc)	Top Contributing Author (#doc)	Most Used Journal (#doc)	Most Cited Paper (#cite)
China	2016–2023	196	5130	31	USA (15) and UK (15)	Chinese Academy of Sciences (15)	Zhang, Y. (9), Ren, S. (9), and Liu, Y. (9)	*Journal of Cleaner Production* (20)	Tao et al. [20] (1406)
USA	2013–2023	124	3718	33	China (15)	The University of Tennessee, Knoxville (7)	Huisingh, D. (6)	*Journal of Cleaner Production* (8)	Ren et al. [22] (245)
India	2014–2023	90	1656	21	USA (12)	Jamia Millia Islamia (5)	Atassi, L. (3)	*Advances in Science Technology and Innovation* (3)	Sharma et al. [72] (221)
UK	2013–2023	80	1965	24	China (15)	The University of Manchester (6)	Jagtap, S. (3)	*Economics Management and Financial Markets* (4)	Sharma et al. [72] (221)
Italy	2014–2023	57	913	15	UK (11)	Consiglio Nazionale delle Ricerche (5)	Hassoun, A. (4)	*Proceedings of the Summer School Francesco Turco* (4)	Kissling et al. [73] (164)

The analyses reveal that 160 academic institutions are contributing to enriching the understudied area. Table 2 shows the top five productive institutions publishing research works in recent years. Their productivity is measured by the number of TP, TC, and the document h-index, which is a way of displaying and comparing the productivity and impact of published works. As shown in the table, the Chinese Academy of Sciences ranked first, with 15 publications and 199 total citations, followed by the Ministry of Education China, with 13 publications and 1150 total citations. Interestingly, the Chinese Academy of Sciences collaborated the most with the University of the Chinese Academy of Sciences, while the Ministry of Education China collaborated the most with Northwestern Polytechnical University, implying that the topic has received undivided attention from the chief Chinese institutions. The top contributing author refers to the author who contributed the most reports to the institutions listed in Table 2; Zhang, Y. from the Ministry of Education China and Liu, Y. from Linköpings Universitet both contributed nine published documents, which is the highest number of contributions.

Table 2. Top five productive academic institutions.

Institution	Country	Publication Year	TP	TC	Document h-Index	Most Collaborative Institute (#doc)	Top Contributing Author (#doc)	Most Used Journal (#doc)	Most Cited Paper (#cite)
Chinese Academy of Sciences	China	2017–2022	15	199	8	University of Chinese Academy of Sciences (9)	Che, T. (3) and Pan, X. (3)	*Big Earth Data* (2)	Kuang et al. [74] (37)
Ministry of Education China	China	2017–2023	13	1150	8	Northwestern Polytechnical University (9)	Zhang, Y. (9)	*Journal of Cleaner Production* (6)	Zhang et al. [16] (324)
Norges Teknisk-Naturvitenskapelige Universitet	Norway	2019–2023	13	480	8	INRAE (3)	Bibri, S.E. (6)	*Advances In Science Technology and Innovation* (3)	Kristoffersen et al. [19] (200)
Linköpings Universitet	Sweden	2017–2023	11	1046	8	Ministry of Education China (8)	Liu, Y. (9)	*Journal of Cleaner Production* (6)	Zhang et al. [16] (324)
CNRS Centre National de la Recherche Scientifique	France	2018–2023	10	358	5	Université Fédérale Toulouse Midi-Pyrénées (4)	Belaud, J.P. (2)	n/a	Kissling et al. [73] (164)

The contributing authors have hence been evaluated, as this provides insights into the individual researchers' productivity and contributions to their respective institutions. The total number of documents, amounting to 870, has been contributed by 159 authors. Table 3 provides an overview of the top five prolific authors who have demonstrated remarkable productivity, representing diverse affiliations across five countries—China (with two authors), Sweden, the United States, and Switzerland. Zhang, Y. from Northwestern Polytechnical University ranked first. Upon examining institutional contributions, it becomes apparent that this particular author played a pivotal role in elevating his institution's rank to the highest position among the other 160 academic institutions. The authors' affiliations demonstrate that the primary concentration of the topic is in subject areas relating to Engineering and Computer Science. The distribution of research in different subject areas is displayed in Figure 4, where the top five subject areas with the highest percentage of research publications are Engineering (16.02%), Computer Science (15.38%), Environmental Science (10.52%), Business, Management and Accounting (9.98%), and Social Sciences (8.47%). Comparing the most used journals, it can be seen that the *Journal of Cleaner Production* is the most common one, as it appears as an active journal for four out of five authors (Table 3), suggesting that it is a popular journal among prolific researchers in various fields. Overall, the results indicate that there are 101 journals publishing documents related to the topic. Table 4 provides useful information about the top five active journals in the field. *Sustainability*, with 60 publications, is the journal with the highest number of publications. The table also demonstrates the journals' CiteScore 2021 (highest percentile); it is a metric that measures the average citations received per document published in the journal, and thus indicates the percentile position of the journal compared to other journals in the same category.

Table 3. Top five prolific authors.

Author (h-Index)	Affiliation	Publication Year	TP	TC	Document h-Index	Most Used Journal (#doc)	Most Cited Paper (#cite)
Zhang, Y. (47)	Northwestern Polytechnical University, Xi'an, China	2017–2022	9	1137	8	*Journal of Cleaner Production* (6)	Zhang et al. [16] (324)
Liu, Y. (31)	Linköpings Universitet, Linkoping, Sweden	2017–2023	9	1028	8	*Journal of Cleaner Production* (6)	Zhang et al. [16] (324)
Ren, S. (13)	Xi'an Institute of Posts and Telecommunications, School of Modern Posts, Xi'an, China	2017–2022	9	1027	8	*Journal of Cleaner Production* (5)	Zhang et al. [16] (324)
Huisingh, D. (55)	The University of Tennessee, Knoxville, Knoxville, United States	2017–2020	6	692	6	*Journal of Cleaner Production* (5)	Ren et al. [22] (245)
Bibri, S.E. (24)	Ecole Polytechnique Fédérale de Lausanne, Department of Civil and Environmental Engineering, Lausanne, Switzerland	2019–2022	6	174	3	*Advances in Science Technology and Innovation* (3)	Bibri and Krogstie [75] (81)

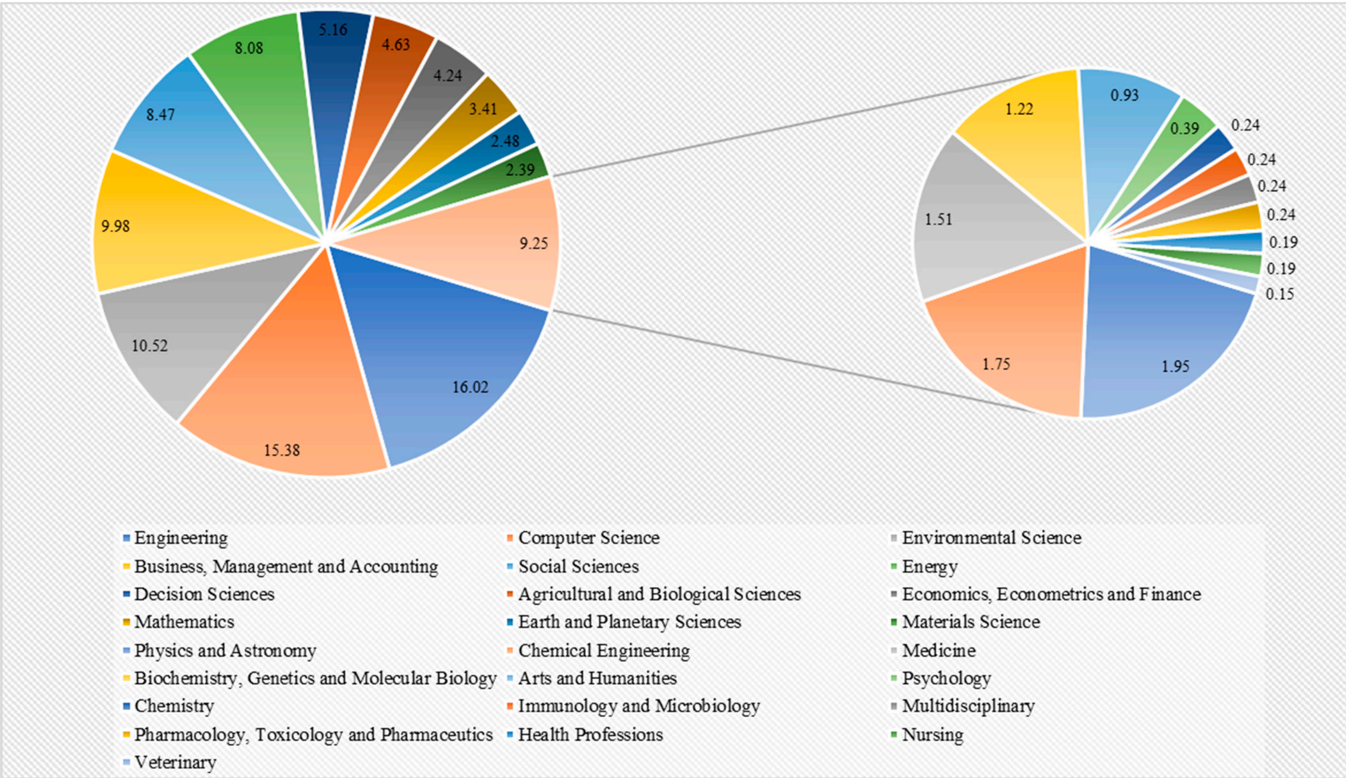


Figure 4. Distribution of research in various subject areas over the years.

Table 4. Top five active journals in the field.

Journal	Publication Year	TP	TC	Document h-Index	CiteScore 2021 (Highest Percentile)	Most Cited Paper (#Cite)—Objective
Sustainability	2017–2023	60	1583	18	5.0 (86th)	Nagy et al. [18] (311)—To examine how businesses in Hungary understand and apply the concept of Industry 4.0 and its tools including IoT, BDA, etc.
Journal of Cleaner Production	2017–2022	33	2383	25	15.8 (98th)	Zhang et al. [16] (324)—To propose an overall architecture of BDA for product lifecycle.

Table 4. *Cont.*

Journal	Publication Year	TP	TC	Document h-Index	CiteScore 2021 (Highest Percentile)	Most Cited Paper (#Cite)—Objective
Journal of Self Governance and Management Economics	2019–2021	14	307	7	5.3 (99th)	Peters et al. [42] (103)—To examine the relationship between product decision-making information systems, real-time BDA, and deep learning-enabled smart process planning in sustainable Industry 4.0.
Procedia CIRP	2014–2022	14	257	8	3.9 (67th)	Bressanelli et al. [76] (90)—To explore the role of digital technologies in a case study of a company utilizing a PSS business model with IoT, and BDA.
Economics Management and Financial Markets	2019–2021	13	284	10	5.1 (95th)	Nica et al. [41] (60)—To present an exploratory analysis on IoT-based real-time production logistics, sustainable industrial value creation, and artificial intelligence-driven BDA in cyber–physical smart manufacturing systems.

Next, the most highly cited papers have been identified up to May 2023, as shown in Table 5, wherein the type of documents in which they were published were journal articles. A journal article undergoes a rigorous peer-review process, where experts in the field review the research for its quality, validity, and relevance before it is accepted for publication. This process helps ensure that the research meets the high standards of academic rigor and contributes to the advancement of knowledge in the field. To this end, the work of Tao et al. [20] is regarded to have the highest sum of citations (1406), and a FWCI of 75.2. The field-weighted citation impact (FWCI) is used to indicate how well cited this document is when compared to similar documents. In addition, the articles in Table 5 demonstrate how they can help achieve sustainable development goals (SDGs) by covering a wide range of topics related to BDA and addressing production sustainability challenges across different industries. By advancing knowledge in these areas, researchers can help support progress toward the SDGs (Figure 5) and thus a more sustainable future.

Table 5. Top ten influential papers.

Title	Type	Publication Year	Authors	TC	FWCI *	Objective	Contribution to SDGs **
Digital twin-driven product design, manufacturing, and service with big data	Journal article	2018	Tao et al. [20]	1406	75.2	To propose a method for product design, manufacturing, and service driven by digital twin, exploring its application methods, frameworks, and future potential through three illustrative cases.	Goal 9
Green innovation and organizational performance: The influence of big data and the moderating role of management commitment and HR practices	Journal article	2019	El-Kassar and Singh [15]	438	43.25	To develop and test a model demonstrating the relationships among green innovation, its drivers, and factors influencing performance and competitive advantage.	Goals 7, 9 and 12
A big data analytics architecture for cleaner manufacturing and maintenance processes of complex products	Journal article	2017	Zhang et al. [16]	324	15.31	To propose an overall architecture of BDA for product lifecycle.	Goals 8, 9 and 12

Table 5. *Cont.*

Title	Type	Publication Year	Authors	TC	FWCI *	Objective	Contribution to SDGs **
The role and impact of Industry 4.0 and the Internet of Things on the business strategy of the value chain: the case of Hungary	Journal article	2018	Nagy et al. [18]	311	15.41	To examine how businesses understand and apply the concept of Industry 4.0 and its tools including IoT, BDA, etc.	Goals 8 and 9
Industry 4.0: A solution towards technology challenges of sustainable business performance	Journal article	2019	Haseeb et al. [21]	286	50.14	To identify and examine elements of Industry 4.0 including BDA, IoT, etc. to develop sustainable business performance.	Goals 9 and 17
Industry 4.0 and sustainability implications: A scenario-based analysis of the impacts and challenges	Journal article	2018	Bonilla et al. [17]	270	13.76	To examine and discuss the sustainability, impact, and challenges of Industry 4.0 and its related technologies, including BDA, IoT, etc. from four dissimilar scenarios.	Goals 8, 9, 12 and 17
A comprehensive review of big data analytics throughout product lifecycle to support sustainable smart manufacturing: A framework, challenges and future research directions	Journal article	2019	Ren et al. [22]	245	13.78	To present a comprehensive overview of BDA in smart manufacturing and propose a product lifecycle-based framework.	Goals 9 and 12
Big Data Analytics for Dynamic Energy Management in Smart Grids	Journal article	2015	Diamant-oulakis et al. [14]	240	10.15	To 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.	Goals 7, 9 and 12
Big data analytics as an operational excellence approach to enhance sustainable supply chain performance	Journal article	2020	Bag et al. [23]	223	18.03	To assess the significance of BDA capability for enhancing sustainable supply chain performance using the dynamic capability theory.	Goals 9, 12 and 17
The smart circular economy: A digital-enabled circular strategies framework for manufacturing companies	Journal article	2020	Kristoffersen et al. [19]	200	10.99	To present 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.	Goals 8, 9, 12 and 17

* The field-weighted citation impact shows how well cited this document is when compared to similar documents.
** Goal 7—Affordable and clean energy. Goal 8—Decent work and economic growth. Goal 9—Industry, innovation and infrastructure. Goal 12—Responsible consumption and production. Goal 17—Partnership for the goals.

BDA is poised to have a substantial impact across multiple domains: research and development, manufacturing, customer service, maintenance and repair, technical support for overhauls, recycling, and remanufacturing. Its efficacy lies in its ability to drive the implementation of cleaner production practices and foster the growth of sustainable production and consumption [16]. By effectively collecting and analyzing diverse data generated throughout the entire lifecycle of a product, BDA offers systematic guidance for related production activities. Moreover, it assists enterprise managers in resolving operational and decision making challenges by uncovering novel value through relationships and statistical patterns within various datasets [15,20,54]. Leveraging BDA to extract value from big data throughout the lifecycle and employing sterilization as a business strategy represents a potential future trend for manufacturing enterprises, enabling the creation of additional value and augmenting sustainability [22,55,56]. With the integration of BDA competencies, organizations can revolutionize their approach to tracking and managing products, ensuring efficient utilization of resources and minimizing waste. The ability to gather and analyze vast amounts of data allows for proactive decision making, identifying potential issues before they escalate, and facilitating timely interventions. Thus, this comprehensive monitoring empowers businesses to optimize their product lifecycle, improving efficiency, reducing costs, and contributing to sustainable practices. The insights derived from BDA can drive innovation and inform strategic planning, enabling companies to stay competitive in a rapidly evolving market landscape [14,23].

Figure 5. The 2030 Sustainable Development Goals (https://www.un.org/sustainabledevelopment/sustainable-development-goals/, accessed on 1 August 2023) mapped to the topic.

All these studies are beneficial when seeking to realize how BDA can contribute to developing sus-products. In general, such development is achieved through the clustering, evaluation, and improvement of the interconnected indicators [32], which are described as variables or characteristics that indicate the state or behavior (i.e., content or performance indicators) of a model, and subsequently necessitate the application of a metric in order to compare them to a baseline or a sustainable outcome [29,77]. Figure 6 reveals the major indicators influencing sus-products' development in the form of a Venn diagram, where the collaboration generated by the overlap among the economic, environmental, and societal indicators is designed to accomplish sustainability at the product level. To summarize, the literature indicates a progressively growing interest in the utilization of BDA for the development of sus-products, but none of it explicitly investigates and assesses the topic in terms of the aforementioned indicators shown in Figure 6. By employing an analytical approach, as elaborated in the subsequent section, this research aims to narrow this gap, and, consequently, enrich the area that could help achieve the SDGs 7, 8, 9, 12, and 17, as depicted in Figure 5. Such evaluations can provide evidence-based insights for stakeholders to guide sustainable development efforts.

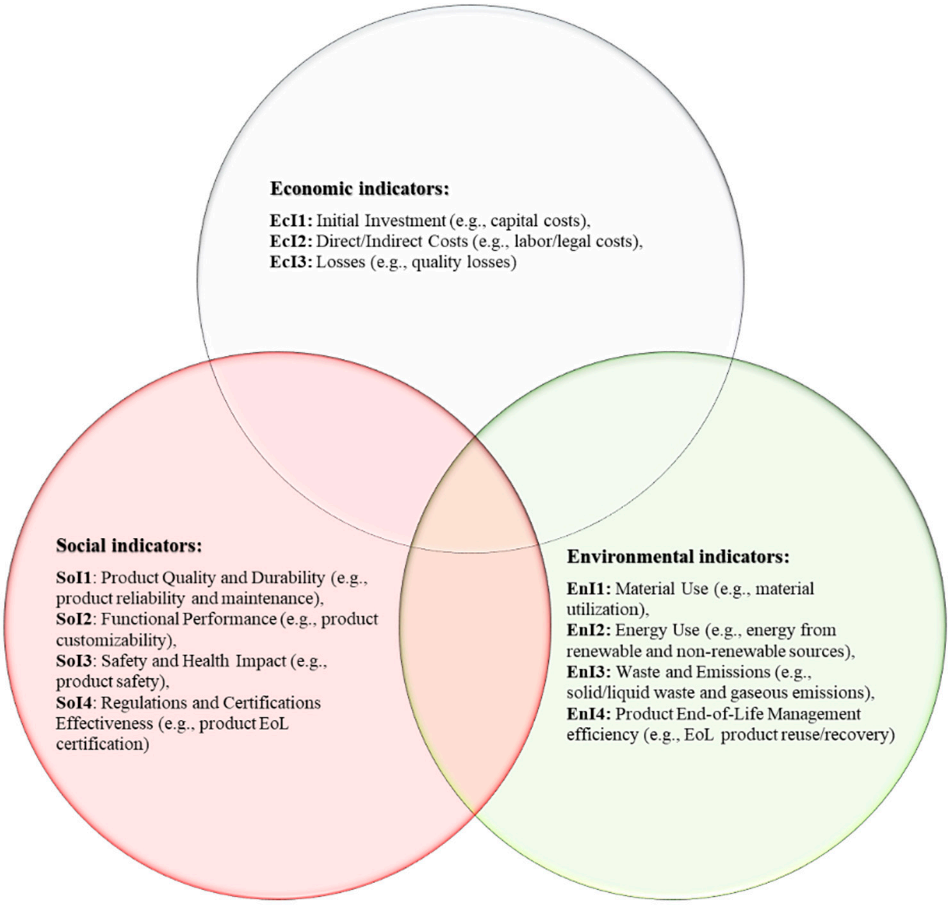


Figure 6. Venn diagram of major indicators influencing sustainable product development (indicators were taken from the following primary references: Jawahir et al. [30], De Silva et al. [31], Shuaib et al. [32], and Jayal et al. [34]).

5. Results and Discussion on the Analysis: Empirical Contribution and Implications

The applied methods assist in tackling two primary research inquiries: offering diverse implications for stakeholders such as policy makers, decision makers, and individuals interested in comprehending the scientific progress of BDA research for sus-products and more significantly, assessing the potential of BDA in fostering the development of sus-products with respect to product sustainability indicators in the realms of economy, environment, and society (Figure 6).

Prior to delving into the application of the Fuzzy-TOPSIS method (Section 3.2), a survey was applied following the approach outlined by Forza [60], as it is utilized in conjunction with pragmatic methods to explore concepts within the emerging field. The objective is to narrow the divide between theory and practice concerning the identified product sustainability indicators, enhancing the practicality of research for practitioners, and elevating the scholarly status of the evolving field [60]. Accordingly, the application of a six-point Likert scale enabled the assignment of values to responses, with 0 indicating 'not applicable', 1 representing 'very low', 2 signifying 'low', 3 demonstrating 'moderate', 4 denoting 'high', and 5 designating 'very high'. The questionnaire consisted of four sections. The first section of the questionnaire inquired about the backgrounds of the respondents. The subsequent sections were designed correspondingly to evaluate the contributory level of BDA to each of the product sustainability aspects (Figure 6) in the context of automotive manufacturing, since such industries have been under obligations to significantly enhance their sustainable performance due to the harmful impact of their unsustainable products and protocols on the environment and society. To counteract such harm, there is a pressing need for the automotive manufacturing industry to transition toward sustainable practices. According to Bai et al. [78] and Lee et al. [59], automotive manufacturers are obliged to mitigate their environmental impact and enhance ecological efficiency by adopting comprehensive environmental initiatives across all stages of the manufacturing process. While sustainability initiatives in the automotive industry are garnering increasing attention and scholarly focus, there remains a need for greater clarity and specificity in their implementation and outcomes [6,35]. Hence, this study found the automotive industry to be an apt context for the investigation due to its substantial size and ecological impact. This preference was motivated by the ongoing evolution of BDA in this sector over the years.

To ensure a sound survey, the data were collected from the vantage points of seasoned technologists, who hold significant positions as stakeholders in tackling technological challenges in organizations. Understanding their perceptions in this context is crucial, as it grants policymakers a more profound insight into the evaluation process from the standpoint of one of their key stakeholder groups. Following the development of the questionnaire, a distribution process was initiated to reach out to 200 seasoned experts identified as prospective professional technologists eligible to participate in the survey. Within a span of 41 days from the commencement date, all responses were successfully collected. Out of the 200 questionnaires distributed, a total of 93 were completed, resulting in a response rate of 46.5%, which is deemed satisfactory [58]. The gender distribution was almost equal, with 52.7% male and 47.3% female. The respondents' age groups were mostly in the 36–45 range (63.4%), followed by 26–35 (22.6%), and above 46 (14.0%). In terms of the current level of study, most respondents were pursuing a PhD (62.4%), followed by Master's (20.4%) and Bachelor's (17.2%) degrees. The majority of respondents were in academic positions (55.9%), while 44.1% were in industry positions. Regarding years of experience in the current position, 54.8% had 5 to 10 years of experience, while 45.2% had more than 10 years of experience. In terms of professional technologist experience, the highest percentage of respondents (42%) had 5 to 10 years of experience, followed by more than 10 years (24.7%), 3 to 5 years (20.4%), and less than 3 years (12.9%). Following the data collection process, a reliability test is performed to assess the dependability of the instrument and the gathered data, ensuring their suitability for subsequent analysis. Within the survey research domain, the Cronbach coefficient alpha is widely employed as the predominant method to evaluate the internal reliability of scale indicators, as supported by existing literature [60]. In this study, the reliability test (alpha value) was found to be 0.89, exceeding the recommended value of 0.60 [58].

As discussed earlier, the participants were assigned the responsibility of evaluating the contributory level of BDA to each of the product sustainability aspects (see Figure 6). Consequently, an average mean value [60] was applied to demonstrate the contributory level in this study. The findings revealed that the mean value for the economic aspect is 4.15, for the environmental aspect is 4.37, and for the social aspect is 3.92. Thus, the environmental aspect had the highest mean value, suggesting that the respondents perceived that BDA could considerably contribute to this aspect of sus-products. The findings provide valuable insights for manufacturers interested in leveraging BDA for the development of sus-products. However, the results also imply a critique of the study conducted by Bai et al. [78], as they primarily stressed utilizing BDA to address social sustainability issues.

To further investigate in what terms BDA might contribute to developing sus-products in each of the aspects (Figure 6), the method of Fuzzy-TOPSIS was accordingly applied. As such, the three major professional technologists (P.Tech.1, P.Tech.2, and P.Tech.3) out of 93, possessing over a decade of automotive manufacturing management experience, were entrusted with expressing their opinions on the importance weights of the eleven indicators, using linguistic variables including very low, low, etc. (Table 6), and independently rating the indicators of BDA via linguistic variables such as very poor, poor, etc. (Table 7) following references [28,61,63].

Table 6. Linguistic variables for the relative importance weights of eleven indicators.

Linguistic Variable	Code	Fuzzy Number
Very low	VL	(0, 0, 0.1)
Low	L	(0, 0.1, 0.3)
Medium low	ML	(0.1, 0.3, 0.5)
Medium	M	(0.3, 0.5, 0.7)
Medium high	MH	(0.5, 0.7, 0.9)
High	H	(0.7, 0.9, 1.0)
Very high	VH	(0.9, 1.0, 1.0)

Table 7. Linguistic variables for the ratings.

Linguistic Variable	Code	Fuzzy Number
Very poor	VP	(0, 0, 1)
Poor	P	(0, 1, 3)
Medium poor	MP	(1, 3, 5)
Fair	F	(3, 5, 7)
Medium good	MG	(5, 7, 9)
Good	G	(7, 9, 10)
Very good	VG	(9, 10, 10)

Tables 8 and 9 show the assessment information provided by the three P.Techs, where aggregated fuzzy numbers are obtained by averaging the fuzzy opinions of the three P.Techs. Table 9 presents a demonstration of the normalized and weighted fuzzy decision matrix, as well as the closeness coefficient of BDA (CCBDA). The findings of analyses are generally highlighted in Table 9, where the results indicate that EnI4 (product end-of-life management efficiency) has the highest closeness coefficient of 0.787, followed by SoI1 (product quality and durability) with a coefficient of 0.579, and SoI2 (functional performance) with a coefficient of 0.523. Thus, the contributory rank of BDA to each indicator—the higher the rank, the higher the perceived level of contribution—reveals that EnI4 has the highest contributory rank, followed by SoI1, with a rank of 2, and SoI2, with a rank of 3. These findings cannot be compared to previous BDA research, as this study is the primary empirical investigation focusing on BDA in the context of developing sustainable products using product sustainability indicators. This underscores the distinctive contribution of this investigation to the topic; however, these empirical findings can provide supporting evidence for the theoretical studies highlighting the contribution of BDA to improving EnI4 [22,36,54]. These discoveries can be embraced by policymakers and/or decision-makers to promote the adoption of BDA for sus-products through targeted policy interventions, as the analytical approach is rooted in the criteria of product sustainability, rather than solely considering a broad sustainability perspective, underscoring its aptness for informing specific strategic decisions.

Table 8. Indicators' importance and aggregated fuzzy weights.

Indicator	Sustainability Aspects	Desired Degree	Experts' Linguistic Valuation			Aggregated Fuzzy Weight
			P.Tech.1	P.Tech.2	P.Tech.3	
EcI1	Eco	Min	H	VH	VH	(0.83, 0.96, 1.00)
EcI2	Eco	Min	H	VH	VH	(0.83, 0.96, 1.00)
EcI3	Eco	Min	VH	H	VH	(0.83, 0.96, 1.00)
EnI1	Env	Min	VH	H	VH	(0.83, 0.96, 1.00)
EnI2	Env	Min	MH	MH	H	(0.56, 0.76, 0.93)
EnI3	Env	Min	H	H	VH	(0.76, 0.93, 1.00)
EnI4	Env	Max	H	H	VH	(0.76, 0.93, 1.00)
SoI1	Soc	Max	VH	H	VH	(0.83, 0.96, 1.00)
SoI2	Soc	Max	VH	H	VH	(0.83, 0.96, 1.00)
SoI3	Soc	Max	H	MH	H	(0.63, 0.83, 0.96)
SoI4	Soc	Max	H	MH	H	(0.63, 0.83, 0.96)

Table 9. BDA's importance, normalized fuzzy weights and contribution to the indicators.

Indicator	Big Data Analytics (BDA)							
	P.Tech.1	P.Tech.2	P.Tech.3	Aggregation	Normalization	Normalized Fuzzy Weight	CC_{BDA}	Contributory Rank
EcI1	M	MP	M	(2.33, 4.33, 6.33)	(0.05, 0.07, 0.14)	(0.04, 0.06, 0.14)	0.089	9
EcI2	MP	P	P	(0.33, 1.66, 3.66)	(0.09, 0.19, 1.00)	(0.07, 0.18, 1.00)	0.439	5
EcI3	MP	P	MP	(0.66, 2.33, 4.33)	(0.07, 0.14, 0.50)	(0.05, 0.13, 0.50)	0.269	7
EnI1	M	M	MG	(3.66, 5.66, 7.66)	(0.04, 0.05, 0.09)	(0.03, 0.05, 0.09)	0.060	10
EnI2	M	M	MG	(3.66, 5.66, 7.66)	(0.04, 0.05, 0.09)	(0.02, 0.04, 0.08)	0.050	11
EnI3	P	MP	P	(0.33, 1.66, 3.66)	(0.09, 0.19, 1.00)	(0.07, 0.17, 1.00)	0.446	4
EnI4	VG	VG	VG	(9.00,10.0,10.00)	(0.90, 1.00, 1.00)	(0.60, 0.90, 1.00)	0.787	1
SoI1	MG	M	MG	(4.33, 6.33, 8.33)	(0.43, 0.63, 0.83)	(0.35, 0.60, 0.83)	0.579	2
SoI2	MG	M	M	(3.66, 5.66, 7.66)	(0.36, 0.56, 0.76)	(0.29, 0.53, 0.76)	0.523	3
SoI3	MP	MP	MP	(1.00, 3.00, 5.00)	(0.10, 0.30, 0.50)	(0.06, 0.24, 0.48)	0.292	6
SoI4	P	P	MP	(0.33, 1.66, 3.66)	(0.03, 0.16, 0.36)	(0.02, 0.13, 0.34)	0.202	8

6. Limitations and Future Research Directions

Despite its contribution, this study has limitations that could guide future research. Given the increasing global research interest in the field of BDA for sus-products, it would be beneficial to conduct subsequent bibliometric and network analyses that explore the latest trends and tools. This can help researchers and practitioners stay up-to-date with the rapidly evolving field and identify new opportunities for applying BDA to developing sus-products. The research discussed in this study pertains to BDA for sustainable products until May 2023; it is critical to conduct the same analyses again in the coming years, using updated studies to compare the new findings with those presented in this review. Moreover, the analysis documented is restricted to the Scopus database, which may give different insights compared to other databases like Web of Science.

The empirical findings primarily focus on investigating BDA for sus-products in the context of automotive manufacturing; future studies can extend this research to other industries. Additionally, the implementation of BDA for developing sus-products faces various challenges that require attention. To this end, the identified indicators can be further surveyed to understand their interdependencies, develop measurement frameworks, and explore strategies to optimize their contributions to sus-products' development.

Following the fuzzy-based findings, which are based on product sustainability indicators in the realms of economy, environment, and society (and not merely from a general perspective of sustainability), future studies should consider such bi-focal lenses when developing analytical approaches. To address uncertainty, other theories like the grey system theory can also be used. To ensure robustness, sensitivity analyses or variations in parameter settings could be explored, but were not included in this study. The potential for future research is vast, with opportunities to explore and analyze BDA for other critical elements, i.e., sustainable processes and/or systems, across various contexts. These elements have explicitly been discussed by Gholami et al. [3,36].

7. Conclusions and Final Considerations

This article presents a particular perspective that is of significant importance to sustainable development and has just started to develop: big data analytics for sustainable products. Accordingly, it addresses the formulated research questions, aiming to boost the values of economic, environmental, and social sustainability of the fourth paradigm of science in the context of sustainable production; yet, the integration and systematization of existing knowledge on the topic, particularly the analysis of the matter in terms of product sustainability indicators, is scarce. As such, this study uses a bibliometric approach to review scientific data to shed light on the topic. The Fuzzy-TOPSIS method is then applied to further analyze the issue based on the respective indicator set in each of the sustainability aspects.

Following the research questions, the theoretical outcomes derived from the bibliometric analysis revealed that a total of 870 documents written in English over 12 years (2012–2023) had been published in various types, with journal papers covering 46.67% of them. The review demonstrated an increasing global research interest in an understudied area, which has been evident from the rapid increase in annual publications and citations since 2017. Among the top countries contributing to the topic, China and the US account for a significant number of documents, covering 14.1% and 8.92% of the global total publications, respectively. Active collaboration between researchers from China, the US, and the UK was also observed in various institutions. In total, around 160 academic institutions and 159 authors have enriched the field, primarily in subject areas relating to Engineering and Computer Science. The influential papers, covering a wide range of topics related to BDA for sus-products, have been further summarized. The major indicators influencing sus-products' development were accordingly discussed and depicted. By advancing knowledge in the field, researchers may support progress toward the SDGs, including Goal 7 (affordable and clean energy), Goal 8 (decent work and economic growth), Goal 9 (industry, innovation and infrastructure), Goal 12 (responsible consumption and production), and Goal 17 (partnership for the goals). Such evaluations can provide evidence-based insights for stakeholders to guide sustainable development efforts.

The empirical findings demonstrated that EnI4 (product end-of-life management efficiency) has the highest closeness coefficient of 0.787, followed by SoI1 (product quality and durability), SoI2 (functional performance), EnI3 (waste and emissions), and EcI2 (direct/indirect costs) with coefficients of 0.579, 0.523, 0.446, and 0.439, respectively. In other words, EnI4, representing an environmental indicator of sus-products, has the highest contributory rank in total. Considering social and economic aspects, SoI2 and EcI2 have the highest contributory ranks in developing sus-products using BDA. Such research and analysis offer valuable insights to stakeholders such as policy makers, decision makers, and individuals seeking a deeper understanding of big data analytics and its contribution to developing sus-products in terms of product sustainability indicators in the realms of economy, environment, and society.

Author Contributions: Conceptualization, H.G.; methodology, H.G.; software, H.G.; validation, H.G.; formal analysis, H.G.; investigation, H.G.; resources, H.G.; data curation, H.G.; writing—original draft preparation, H.G. and J.K.Y.L.; writing—review and editing H.G., J.K.Y.L. and A.A.; visualization, H.G.; supervision, H.G.; project administration, H.G.; funding acquisition, H.G. All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported by the Face Foundation through the Thomas Jefferson Fund—Make Our Planet Great Again—under the SUSTAIN project, which is a joint American–French research initiative.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data will be made available on request.

Acknowledgments: The authors acknowledge the UMR 6158 LIMOS lab at Mines Saint-Etienne for the support.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. WCED. *Our Common Future*, 3rd ed.; Oxford University Press: Oxford, UK, 1987.
2. UN. *Agenda 21. The United Nations Programme of Action from Rio*; Unite Nations: New York, NY, USA, 1993.
3. Gholami, H.; Abdul-Nour, G.; Sharif, S.; Streimikiene, D. (Eds.) *Sustainable Manufacturing in Industry 4.0: Pathways and Practices*, 1st ed.; Springer Nature: Singapore, 2023.
4. World Bank. *World Development Report 1999/2000*; Oxford University Press: New York, NY, USA, 1999.
5. Constantiou, I.D.; Kallinikos, J. New Games, New Rules: Big Data and the Changing Context of Strategy. *J. Inf. Technol.* **2015**, *30*, 44–57. [CrossRef]
6. Ali, S.; Poulova, P.; Yasmin, F.; Danish, M.; Akhtar, W.; Javed, H.M.U. How Big Data Analytics Boosts Organizational Performance: The Mediating Role of Sustainable Product Development. *J. Open Innov. Technol. Mark. Complex.* **2020**, *6*, 190. [CrossRef]
7. Georgiadou, E.; Angelopoulos, S.; Drake, H. Big Data Analytics and International Negotiations: Sentiment Analysis of Brexit Negotiating Outcomes. *Int. J. Inf. Manag.* **2020**, *51*, 102048. [CrossRef]
8. Mikalef, P.; Boura, M.; Lekakos, G.; Krogstie, J. Big data analytics and firm performance: Findings from a mixed-method approach. *J. Bus. Res.* **2019**, *98*, 261–276. [CrossRef]
9. Rizk, A.; Elragal, A. Data science: Developing theoretical contributions in information systems via text analytics. *J. Big Data* **2020**, *7*, 7. [CrossRef]
10. Akter, S.; Wamba, S.F.; Gunasekaran, A.; Dubey, R.; Childe, S.J. How to improve firm performance using big data analytics capability and business strategy alignment? *Int. J. Prod. Econ.* **2016**, *182*, 113–131. [CrossRef]
11. Columbus, L. 84% of Enterprises See Big Data Analytics Changing Their Industries' Competitive Landscapes in the Next Year. 2014. Available online: 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=1db21b517de1 (accessed on 1 May 2023).
12. Johnson, J.S.; Friend, S.B.; Lee, H.S. Big data facilitation, utilization, and monetization: Exploring the 3Vs in a new product development process. *J. Prod. Innov. Manag.* **2017**, *34*, 640–658. [CrossRef]
13. Tan, K.H.; Zhan, Y. Improving new product development using big data: A case study of an electronics company. *R&D Manag.* **2017**, *47*, 570–582.
14. Diamantoulakis, P.D.; Kapinas, V.M.; Karagiannidis, G.K. Big data analytics for dynamic energy management in smart grids. *Big Data Res.* **2015**, *2*, 94–101. [CrossRef]
15. El-Kassar, A.N.; Singh, S.K. Green innovation and organizational performance: The influence of big data and the moderating role of management commitment and HR practices. *Technol. Forecast. Soc. Chang.* **2019**, *144*, 483–498. [CrossRef]
16. Zhang, Y.; Ren, S.; Liu, Y.; Si, S. A big data analytics architecture for cleaner manufacturing and maintenance processes of complex products. *J. Clean. Prod.* **2017**, *142*, 626–641. [CrossRef]
17. Bonilla, S.H.; Silva, H.R.; Terra da Silva, M.; Franco Gonçalves, R.; Sacomano, J.B. Industry 4.0 and sustainability implications: A scenario-based analysis of the impacts and challenges. *Sustainability* **2018**, *10*, 3740. [CrossRef]
18. Nagy, J.; Oláh, J.; Erdei, E.; Máté, D.; Popp, J. The role and impact of Industry 4.0 and the internet of things on the business strategy of the value chain—The case of Hungary. *Sustainability* **2018**, *10*, 3491. [CrossRef]
19. Kristoffersen, E.; Blomsma, F.; Mikalef, P.; Li, J. The smart circular economy: A digital-enabled circular strategies framework for manufacturing companies. *J. Bus. Res.* **2020**, *120*, 241–261. [CrossRef]
20. Tao, F.; Cheng, J.; Qi, Q.; Zhang, M.; Zhang, H.; Sui, F. Digital twin-driven product design, manufacturing and service with big data. *Int. J. Adv. Manuf. Technol.* **2018**, *94*, 3563–3576. [CrossRef]
21. Haseeb, M.; Hussain, H.I.; Ślusarczyk, B.; Jermsittiparsert, K. Industry 4.0: A solution towards technology challenges of sustainable business performance. *Soc. Sci.* **2019**, *8*, 154. [CrossRef]

22. Ren, S.; Zhang, Y.; Liu, Y.; Sakao, T.; Huisingh, D.; Almeida, C.M. A comprehensive review of big data analytics throughout product lifecycle to support sustainable smart manufacturing: A framework, challenges and future research directions. *J. Clean. Prod.* **2019**, *210*, 1343–1365. [CrossRef]
23. Bag, S.; Wood, L.C.; Xu, L.; Dhamija, P.; Kayikci, Y. Big data analytics as an operational excellence approach to enhance sustainable supply chain performance. *Resour. Conserv. Recycl.* **2020**, *153*, 104559. [CrossRef]
24. Dwivedi, Y.K.; Highes, L.; Kar, A.K.; Baabdullah, A.M.; Grover, P.; Abbas, R.; Andreini, D.; Abumoghli, I.; Barlette, Y.; Bunker, D.; et al. Climate change and COP26: Are digital technologies and information management part of the problem or the solution? An editorial reflection and call to action. *Int. J. Inf. Manag.* **2022**, *63*, 102456. [CrossRef]
25. Kar, A.K.; Dwivedi, Y.K. Theory building with big data-driven research—Moving away from the "What" towards the "Why". *Int. J. Inf. Manag.* **2020**, *54*, 102205. [CrossRef]
26. Broadus, R. Toward a definition of bibliometrics. *Scientometrics* **1987**, *12*, 373–379. [CrossRef]
27. Abu, F.; Gholami, H.; Saman, M.Z.M.; Zakuan, N.; Sharif, S.; Streimikiene, D. Pathways of lean manufacturing in wood and furniture industries: A bibliometric and systematic review. *Eur. J. Wood Wood Prod.* **2021**, *79*, 753–772. [CrossRef]
28. Chen, C.T. Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets Syst.* **2000**, *114*, 1–9. [CrossRef]
29. Gholami, H.; Hashemi, A.; Lee, J.K.Y.; Abdul-Nour, G.; Salameh, A.A. Scrutinizing state-of-the-art I4.0 technologies toward sustainable products development under fuzzy environment. *J. Clean. Prod.* **2022**, *377*, 134327. [CrossRef]
30. Jawahir, I.S.; Dillon, O.W.; Rouch, K.E.; Joshi, K.J.; Venkatachalam, A.; Jaafar, I.H. Total Life-Cycle Considerations in Product Design for Sustainability: A Framework for Comprehensive Evaluation. In Proceedings of the 10th International Research/Expert Conference, Barcelona, Spain, 11–15 September 2006.
31. De Silva, N.; Jawahir, I.S.; Dillon, O., Jr.; Russell, M. A new comprehensive methodology for the evaluation of product sustainability at the design and development stage of consumer electronic products. *Int. J. Sustain. Manuf.* **2009**, *1*, 251–264. [CrossRef]
32. Shuaib, M.; Seevers, D.; Zhang, X.; Badurdeen, F.; Rouch, K.E.; Jawahir, I.S. Product sustainability index (ProdSI) a metrics-based framework to evaluate the total life cycle sustainability of manufactured products. *J. Ind. Ecol.* **2014**, *18*, 491–507. [CrossRef]
33. Hapuwatte, B.M.; Jawahir, I.S. Closed-loop sustainable product design for circular economy. *J. Ind. Ecol.* **2021**, *25*, 1430–1446. [CrossRef]
34. Jayal, A.D.; Badurdeen, F.; Dillon, O.W., Jr.; Jawahir, I.S. Sustainable manufacturing: Modeling and optimization challenges at the product, process and system levels. *CIRP J. Manuf. Sci. Technol.* **2010**, *2*, 144–152. [CrossRef]
35. Ahmad, S.; Wong, K.Y.; Tseng, M.L.; Wong, W.P. Sustainable product design and development: A review of tools, applications and research prospects. *Resour. Conserv. Recycl.* **2018**, *132*, 49–61. [CrossRef]
36. Gholami, H.; Abu, F.; Lee, J.K.Y.; Karganroudi, S.S.; Sharif, S. Sustainable Manufacturing 4.0—Pathways and Practices. *Sustainability* **2021**, *13*, 13956. [CrossRef]
37. Stock, T.; Seliger, G. Opportunities of sustainable manufacturing in industry 4.0. *Procedia CIRP* **2016**, *40*, 536–541. [CrossRef]
38. Faulkner, W.; Badurdeen, F. Sustainable Value Stream Mapping (Sus-VSM): Methodology to visualize and assess manufacturing sustainability performance. *J. Clean. Prod.* **2014**, *85*, 8–18. [CrossRef]
39. Jamil, N.; Gholami, H.; Mat Saman, M.Z.; Streimikiene, D.; Sharif, S.; Zakuan, N. DMAIC-based approach to sustainable value stream mapping: Towards a sustainable manufacturing system. *Econ. Res.-Ekon. Istraživanja* **2020**, *33*, 331–360. [CrossRef]
40. Lee, J.K.Y.; Gholami, H.; Saman, M.Z.M.; Ngadiman, N.H.A.B.; Zakuan, N.; Mahmood, S.; Omain, S.Z. Sustainability-oriented application of value stream mapping: A review and classification. *IEEE Access* **2021**, *9*, 68414–68434. [CrossRef]
41. Nica, E.; Stan, C.I.; Luțan, A.G.; Oașa, R.Ș. Internet of things-based real-time production logistics, sustainable industrial value creation, and artificial intelligence-driven big data analytics in cyber-physical smart manufacturing systems. *Econ. Manag. Financ. Mark.* **2021**, *16*, 52–63.
42. Peters, E.; Kliestik, T.; Musa, H.; Durana, P. Product decision-making information systems, real-time big data analytics, and deep learning-enabled smart process planning in sustainable industry 4.0. *J. Self-Gov. Manag. Econ.* **2020**, *8*, 16–22.
43. Vinodh, S.; Ben Ruben, R.; Asokan, P. Life cycle assessment integrated value stream mapping framework to ensure sustainable manufacturing: A case study. *Clean Technol. Environ. Policy* **2016**, *18*, 279–295. [CrossRef]
44. Cox, M.; Ellsworth, D. Managing big data for scientific visualization. *ACM Siggraph* **1997**, *97*, 21–38.
45. Einav, L.; Levin, J. The data revolution and economic analysis. *Innov. Policy Econ.* **2013**, *14*, 1–24.
46. O'Leary, D.E. Artificial intelligence and big data. *IEEE Intell. Syst.* **2013**, *28*, 96–99. [CrossRef]
47. Goes, P. Big data and IS research. *Mis Q.* **2014**, *38*, 3–8.
48. Laney, D. 3D data management: Controlling data volume, velocity and variety. *META Group Res. Note* **2001**, *6*, 1–4.
49. Gantz, J.; Reinsel, D. Extracting value from chaos. *IDC Iview* **2011**, *1142*, 1–12.
50. Zikopoulos, P.; Deroos, D.; Parasuraman, K.; Deutsch, T.; Giles, J.; Corrigan, D. *Harness the Power of Big Data the IBM Big Data Platform*; McGraw Hill Professional: New York, NY, USA, 2012.
51. Kwon, O.; Lee, N.; Shin, B. Data quality management, data usage experience, and acquisition intention of big data analytics. *Int. J. Inf. Manag.* **2014**, *34*, 387–394. [CrossRef]
52. Awan, U.; Shamim, S.; Khan, Z.; Zia, N.U.; Shariq, S.M.; Khan, M.N. Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance. *Technol. Forecast. Soc. Chang.* **2021**, *168*, 120766. [CrossRef]

53. Wang, J.; Xu, C.; Zhang, J.; Zhong, R. Big data analytics for intelligent manufacturing systems: A review. *J. Manuf. Syst.* **2021**, *62*, 738–752. [CrossRef]
54. Li, J.; Tao, F.; Cheng, Y.; Zhao, L. Big data in product lifecycle management. *Int. J. Adv. Manuf. Technol.* **2015**, *81*, 667–684. [CrossRef]
55. Opresnik, D.; Taisch, M. The value of big data in servitization. *Int. J. Prod. Econ.* **2015**, *165*, 174–184. [CrossRef]
56. Tukker, A. Product services for a resource-efficient and circular economy—A review. *J. Clean. Prod.* **2015**, *97*, 76–91. [CrossRef]
57. Pritchard, J. Statistical bibliography or bibliometrics? *J. Doc.* **1969**, *25*, 348–349.
58. Letchumanan, L.T.; Gholami, H.; Yusof, N.M.; Ngadiman, N.H.A.B.; Salameh, A.A.; Štreimikienė, D.; Cavallaro, F. Analyzing the Factors Enabling Green Lean Six Sigma Implementation in the Industry 4.0 Era. *Sustainability* **2022**, *14*, 3450. [CrossRef]
59. Lee, J.K.Y.; Gholami, H.; Medini, K.; Salameh, A.A. Hierarchical analysis of barriers in additive manufacturing implementation with environmental considerations under uncertainty. *J. Clean. Prod.* **2023**, *408*, 137221. [CrossRef]
60. Forza, C. Survey research in operations management: A process-based perspective. *Int. J. Oper. Prod. Manag.* **2002**, *22*, 152–194. [CrossRef]
61. Hwang, C.L.; Yoon, K. *Multiple Attribute Decision Making*; Springer: Berlin/Heidelberg, Germany, 1981.
62. Kumar, N.; Kumar, G.; Singh, R.K. Big data analytics application for sustainable manufacturing operations: Analysis of strategic factors. *Clean Technol. Environ. Policy* **2021**, *23*, 965–989. [CrossRef]
63. Koyuncu, C.A.; Aydemir, E.; Başarır, A.C. Selection Industry 4.0 maturity model using fuzzy and intuitionistic fuzzy TOPSIS methods for a solar cell manufacturing company. *Soft Comput.* **2021**, *25*, 10335–10349. [CrossRef]
64. Nara, E.O.B.; da Costa, M.B.; Baierle, I.C.; Schaefer, J.L.; Benitez, G.B.; do Santos, L.M.A.L.; Benitez, L.B. Expected impact of industry 4.0 technologies on sustainable development: A study in the context of Brazil's plastic industry. *Sustain. Prod. Consum.* **2021**, *25*, 102–122. [CrossRef]
65. Zadeh, L.A. Fuzzy sets. *Inf. Control* **1965**, *8*, 338–353. [CrossRef]
66. Bellman, R.E.; Zadeh, L.A. Decision-making in a fuzzy environment. *Manag. Sci.* **1970**, *17*, 141–164. [CrossRef]
67. Wilson, L.; Goh, T.T.; Wang, W.Y.C. Big Data Management Challenges in a Meteorological Organisation. *Int. J. E-Adopt. (IJEA)* **2012**, *4*, 1–14. [CrossRef]
68. Saguy, I.S.; Singh, R.P.; Johnson, T.; Fryer, P.J.; Sastry, S.K. Challenges facing food engineering. *J. Food Eng.* **2013**, *119*, 332–342. [CrossRef]
69. Kwac, J.; Rajagopal, R. Demand response targeting using big data analytics. In Proceedings of the 2013 IEEE International Conference on Big Data, Silicon Valley, CA, USA, 6–9 October 2013; Volume 6691643, pp. 683–690.
70. Tomic, S.D.K.; Fensel, A. OpenFridge: A platform for data economy for energy efficiency data. In Proceedings of the 2013 IEEE International Conference on Big Data, Silicon Valley, CA, USA, 6–9 October 2013; Volume 6691686, pp. 43–47.
71. Bernat, S.; Karabag, S.F. Strategic alignment of technology: Organising for technology upgrading in emerging economy firms. *Technol. Forecast. Soc. Chang.* **2019**, *145*, 295–306. [CrossRef]
72. Sharma, R.; Kamble, S.S.; Gunasekaran, A.; Kumar, V.; Kumar, A. A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. *Comput. Oper. Res.* **2020**, *119*, 104926. [CrossRef]
73. Kissling, W.D.; Ahumada, J.A.; Bowser, A.; Fernandez, M.; Fernández, N.; García, E.A.; Hardisty, A.R. Building essential biodiversity variables (EBVs) of species distribution and abundance at a global scale. *Biol. Rev.* **2018**, *93*, 600–625. [CrossRef]
74. Kuang, W.; Zhang, S.; Li, X.; Lu, D. A 30 m resolution dataset of China's urban impervious surface area and green space, 2000–2018. *Earth Syst. Sci. Data* **2021**, *13*, 63–82. [CrossRef]
75. Bibri, S.E.; Krogstie, J. The emerging data-driven Smart City and its innovative applied solutions for sustainability: The cases of London and Barcelona. *Energy Inform.* **2020**, *3*, 5. [CrossRef]
76. Bressanelli, G.; Adrodegari, F.; Perona, M.; Saccani, N. The role of digital technologies to overcome Circular Economy challenges in PSS Business Models: An exploratory case study. *Procedia Cirp.* **2018**, *73*, 216–221. [CrossRef]
77. Ragland, B. Measure, Metric or Indicator: What's the Difference? *Crosstalk* **1995**, *8*, 29–30.
78. Bai, C.; Dallasega, P.; Orzes, G.; Sarkis, J. Industry 4.0 technologies assessment: A sustainability perspective. *Int. J. Prod. Econ.* **2020**, *229*, 107776. [CrossRef]