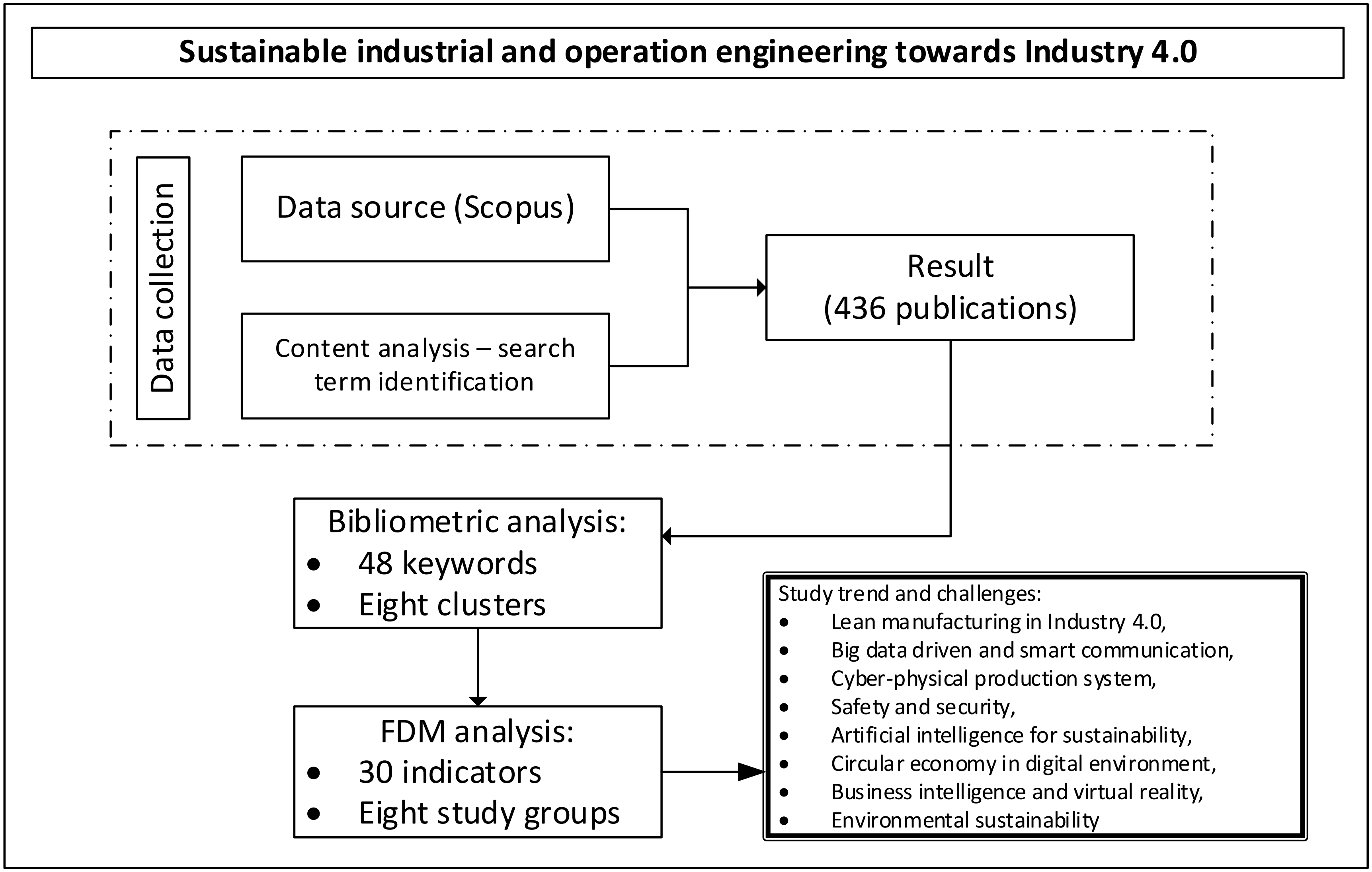
# Sustainable industrial and operation engineering trends and challenges towards Industry 4.0: a data driven analysis

## Abstract

This study supplies contributions to the existing literature with a state-of-the-art bibliometric review of sustainable industrial and operation engineering as the field moves towards Industry 4.0, and guidance for future studies and practical achievements. Although industrial and operation engineering is being promoted forward to sustainability, the systematization of the knowledge that forms firms' manufacturing and operations and encompasses their wide concepts and abundant complementary elements is still absent. This study aims to analyze contemporary sustainable industrial and operations engineering in Industry 4.0 context. The bibliometric analysis and fuzzy Delphi method are proposed. Resulting in a total of 30 indicators that are criticized and clustered into eight study groups, including lean manufacturing in Industry 4.0, cyber-physical production system, big data driven and smart communications, safety and security, artificial intelligence for sustainability, the circular economy in a digital environment, business intelligence and virtual reality, and environmental sustainability.

**Keywords:** Sustainable industrial and operation engineering; Industry 4.0; data driven analysis; fuzzy Delphi method; Bibliometric analysis


Sustainable industrial and operation engineering towards Industry 4.0
Data collection
Data source (Scopus)
Content analysis – search term identification
Result (436 publications)
Bibliometric analysis:
• 48 keywords
• Eight clusters
FDM analysis:
• 30 indicators
• Eight study groups
Study trend and challenges:
• Lean manufacturing in Industry 4.0,
• Big data driven and smart communication,
• Cyber-physical production system,
• Safety and security,
• Artificial intelligence for sustainability,
• Circular economy in digital environment,
• Business intelligence and virtual reality,
• Environmental sustainability

**Sustainable industrial and operation engineering trends and challenges towards Industry 4.0: a data driven analysis**

## 1. Introduction

Sustainable industrial and operation engineering is understood as the map out and production of goods or services, along with the installation and improvement of integrating systems that based on high-quality, high-fidelity, and real-time data, optimize the operational efficiency in manufacturing systems to create sustainable value and economic growth (Junior et al., 2019; Chauhan et al., 2021). This is imperative process to pursue sustainable development goals since it enables the transformation of original materials into desirable products in order to maintain the life quality and modernization while not causing negative environmental impacts like traditional industrial engineering (Enyoghasi and Badurdeen, 2021). Due to the widespread application of new digital technologies, technological capabilities are important for enabling the transition of industrial and operation engineering to a well-organized, stable, efficient, sustainable, and autonomous form. Revolutionary changes in communication techniques have brought capabilities to firms, giving them greater control and monitoring abilities throughout their production procedures and resulting in more effective operations.

Industry 4.0 (I4.0) is a huge technological concept with novel innovations, and involves both digital and physical environment combined by cyber-physical systems (CPS). This accomplishment fosters automated procedures, clever systems having analytical competences through the integration of information technologies, the knowledge from different domains, and a deep interconnection between these domains (Benitez et al., 2020; Onu and Mbohwa, 2021). Alcácer and Cruz-Machado (2019) claimed that I4.0 leads to a digitalization that ends conventional applications, and in which digital technologies allow the connection among objects and enable factory communications to build up the smart manufacturing ecosystem paradigm. Enyoghasi and Badurdeen (2021) and Chauhan et al. (2021) argued that I4.0 is a motivation for sustainable manufacturing in the industrial scenario since it focuses on creating smart products as well as procedures and offering capabilities for product reuse, remanufacture, recycling, and reduction. Therefore, as a consequence of I4.0 penetration, the need for operations planning schemes to cope with the complexity of industrial environments is highlighted.

I4.0 competence has provided firms with ideal opportunities to strengthen sustainable industrial and operations engineering (Sharma et al., 2020). Digitizing manufacturing and business processes by using smarter devices are revealed to offer various advantages, such as effective resource consumption, waste reduction, more efficient control of the production system, output maximization and minimization of resource utilization, overproduction decrease, and energy saving (Kamble et al., 2020). Industrial digitization is proposed to help firms reduce the cost and complexity of waste, achieve energy sustainability across manufacturing processes, diminish defects, and increase the speed of delivering products and services (Ghobakhloo, 2020). Nara et al. (2021) argued the role of I4.0 technologies in catering to better operations control, allowing thereby for real-time adaptation and flexibility based on demands. Thus, integrating I4.0 principles to enhance sustainable industrial and operations engineering enables the maximization of economic, environmental and social benefits (Enyoghasi and Badurdeen, 2021).

In recent years, many studies with regard to engineering and manufacturing topics have been implemented. For example, Alcácer and Cruz-Machado (2019) reviewed I4.0 in manufacturing environments in enabling technologies and based on the smart factory concept, focused on the fashionable and upcoming trends. Junior et al. (2019) presented the industrial engineering problems related to discrete-event entities' behavior and discussed the way to transport and modify these entities in specific processes adopted for the industrial engineering and production management optimal control scheduling throughout the supply chain. However, the studies on sustainable industrial and operation engineering in the I4.0 context are still in the infant phase; in addition, there is a lack of understanding of its effectiveness and only scattered and fragmented mention of practical examples (Rosa et al., 2020). The reviews on the topic of sustainable industrial and operational engineering are still lacking and to provide the scope of opportunities and future study avenues for enhancing sustainability performance, need to be analyzed based on the I4.0 principles and technologies (Enyoghasi and Badurdeen, 2021). A holistic concept overview describing the most appropriate indicators to advance sustainable industrial and operations engineering through the fulfillment of I4.0 is essential.

In the industrial and operation engineering area, the enabling I4.0 technologies like CPSs, big data, IoTs, comprise a complex system with high independence and collaboration that enable the management of this system and the uncertainty of infrastructure delivery (Alcácer and Cruz-Machado, 2019; Oztemel and Gursev, 2020). Since sustainable industrial engineering, operations engineering and I4.0 are wide concepts with abundant complementary indicators, to address the challenges of growing complexity, dynamics, high dimensionality, and disorganized structures, an appropriate tool focusing on the conceptualization of the literature is required. This study suggests a compound method, which includes content along with bibliometric analysis, and a fuzzy Delphi method (FDM), to analyze the contemporary sustainable industrial and operations engineering toward I4.0. Content analysis is used to capture the appropriate information more accurately and enables the recognition of important topics through manual or semiautomatic approaches (Bui et al., 2021). An apparent, static and systematic description of the literature is offered by utilizing bibliometric analysis. Through this method, founded on data from Scopus database and by employing VOSviewer to cater visual outcomes, sustainable industrial and operation engineering indicators are identified (Bui et al., 2020). Furthermore, using a systematic approach, a network analysis in a bibliometric literature review is conducted to enhance future studies by deeply analyzing the associations among papers, keywords, citations to transform thoroughly information in the area into clusters comprising study aspects (Tseng et al., 2021). However, this validation of the indicators can be a highly challenging task, as data provided in many different formats may suffer from various types of ambiguities and inconsistencies. Thus, the FDM is employed to validate more necessary indicators by calculating experts' linguistic evaluations (Tseng et al., 2020).

There are two objectives in this study:

- To examine the fashionable sustainable industrial and operations engineering towards I4.0, as revealed in the literature;
- To determine arguments and trends for improving future studies.

There are two contributions in this study, encompassing (1) useful directions for future studies are suggested by, founded on a review relating to extant literature, providing bibliometric status relating to sustainable industrial and operations engineering toward I4.0; and (2) the decisive matters in need of further investigations are identified for both scholars and practices.

There are 4 remaining sections in this study. Methodologies, data gathering procedure, suggested analysis steps are thoroughly clarified in second section. Bibliometric analysis, content analysis, FDM results are presented in third section. Then, literature review discourse and the argumentation on upcoming study tendencies are shown in fourth section. Finally, last section gives conclusions, impediments and presentations for imminent studies.

## 2. Method

In second section, analysis stages are presented; data gathering, content and bibliometric analysis, FDM are explained rigorously.

### 2.1. Suggested analysis stages

Content and bibliometric analysis, FDM were used to examine sustainable industrial and operation engineering towards I4.0. Lively diagrams were formed and data consistency was ensured by utilizing VOSviewer software.

The analysis stages are presented below.

1. For deductive coding in content analysis, an appropriate search term is determined to gather publication knowledge from database of Scopus.
2. Via utilizing VOSviewer software, bibliometric analysis is carried out for classifying sustainable industrial and operation engineering towards an I4.0 literature structure. Keywords, co-occurrence frequencies and keyword clustering are investigated to indicate implications for future studies.
3. By using a questionnaire, the assessments of experts about suggested indicators are carried out. FDM is employed for validating more vital indicators.

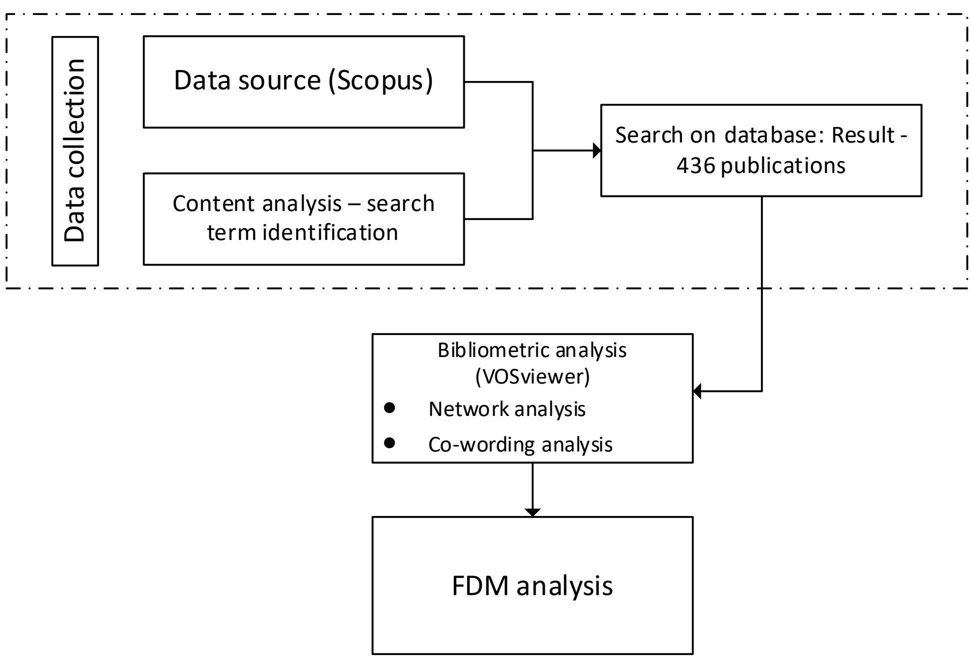



Figure 1. Proposed analysis steps

## 2.2. Data collection

This study employed content analysis to show a detailed and complete overview of the current knowledge concerning sustainable industrial and operation engineering towards I4.0. Content analysis is utilized for completely describing essences of full-text papers and developing an inherent structure for the main papers relating to forming prejudged classes from tightening sizable bundle of texts together with words (Bui et al., 2021). Main characteristic regarding content analysis is to arrange various words within text into much lesser classes. Inductive coding together with deductive coding are two kinds of coding in contemporary employment of content analysis with difference in the means categorizations are obtained. In this study, to find sustainable industrial and operation engineering toward I4.0 literature from the database, the deductive method is first applied for predefined search terms.

On the account of wider publication collection well as more associated bibliometric framework, Scopus database is exerted in this study (Bui et al., 2020). Collected data include various identifiers, such as title, abstract, author, author affiliation, citation record, author keywords, publishing year, country. Thus, Scopus data are appropriate to evaluate the knowledge of sustainable industrial and operation engineering towards I4.0 literature. This study adopts the search boundary limited before December 26, 2020; narrowed to English-language papers together with reviews. Search terms used were the following: "("industr*" OR "operat*") AND ("engineering") AND ("sustain*") AND ("Industry 4.0" OR "smart technology" OR "smart production" OR "smart manufacturing" OR "internet of things" OR "big data" OR "Artificial intelligence" OR "digital" OR "cyber-physical" OR "Cloud*").

## 2.3. Bibliometric analysis

Thanks to bibliometric analysis, a quantitative approach for managing completely growing literature in particular field and offers science mapping, with a focus more on the studies' aims and patterns is provided (Zupic and Cater, 2015). A full picture of the ongoing study scope is presented, explicit along with objective theoretical complex relating to the discipline are provided and the fundamental clusters in the field are disclosed by a comprehensive bibliometric analysis (Rejeb et al., 2020). This method encourages the analysis of current trends in the literature concerning a certain field, and presenting visual information in the results, it provides directions as well as motivations for future studies. VOSviewer software is a suitable tool for dealing with large data amounts and provides many advanced choices to acquire better bibliometric vivid-image outcomes.

### 2.3.1. Network Analysis

Network analysis is adopted to categorize the clusters and show data variety in study area via indicating distinctions among the publications' keywords. While conventional qualitative methods employ some determined biased elements, this method offers an unbiased way to concentrate and conceptualize the literature into clusters (Tseng et al., 2021). Thus, bibliometric together with network analysis are applied for generally discovering potential research areas and, to be exact, structuring sustainable industrial and operation engineering study tendencies. The transferring process of the input data into valuable information is illustrated by bibliometric graphic visuality built from keyword network analysis.

### 2.3.2. Co-Word Analysis

Being an inductive content analysis approach, document keywords are utilized in co-word analysis for communicating the scientific framework of a study field. Word understandings presenting co-occurrence associations in the framework are derived founded on the words' repetitiveness in the paper. A keyword is a unit of a co-word analysis, and for organizing the network relationships among varied keywords, keyword frequencies in set of data are employed (Zupic and Cater, 2015). A keyword is depicted by a node in the structure, the frequentness of keywords' co-occurrence is illustrated by magnitude of each node. Among the keywords, a cluster is built for interpreting these keywords' close interrelationships in comparable forms.

This study made use of VOSviewer with version 1.6.11 for constructing bibliometric systems and investigate the literary framework of sustainable industrial and operation engineering towards I4.0, thus catering learning gaps as promising future study tendencies.

**2.4. Fuzzy Delphi Method**

For solving problem relating to fuzziness of expert judgments, FDM was beneficial in decreasing the interviews' amount along with investigation duration, offered a more comprehensive indication regarding the judgments from experts. With an aim of assuring the reliability of assessment process, 15 experts were contacted in face-to-face meetings (shown in Appendix A). The expert panel consisted of 8 practice experts from various industries with 10 or more years of experience in sustainable industrial and engineering operations, 7 experts from academia with more than 10 years of study experience in related fields.

The importance value of indicator $x$ which is assessed by expert $y$ is $j_{xy} = \left(a_{xy}; b_{xy}; c_{xy}\right)$, in which:

$x = 1,2,3, \dots, n$;

$y = 1,2,3, \dots, m$;

a, b, c: triangular fuzzy numbers adopted from linguistic scale

$a_{xy}, b_{xy}, c_{xy}$: triangular fuzzy numbers of indicator $x$ is assessed by expert $y$

Then, weight $j_x$ of indicator $x$ is $j_x = (a_x; b_x; c_x)$, where:

$a_x = min\left(a_{xy}\right)$;

$b_x = \left(\prod_1^m b_{xy}\right)^{1/m}$; (m: the number of experts)

$c_x = max\left(c_{xy}\right)$,

Table 1 shows the linguistic scale to alter the linguistic terms into triangular fuzzy numbers (TFNs).

Table 1. Transformation table of linguistic terms

| Linguistic terms (performance/importance) | Corresponding triangular fuzzy numbers |
|---|---|
| Extreme | (0.75, 1.0, 1.0) |
| Demonstrated | (0.5, 0.75, 1.0) |
| Strong | (0.25, 0.5, 0.75) |
| Moderate | (0, 0.25, 0.5) |
| Equal | (0, 0, 0.25) |

The convex combination value $E_x$ is counted as follows:

$$E_x = \int(p_x, v_x) = \varepsilon[p_x + (1-\varepsilon)v_x] \quad (1)$$

In which:

$$p_x = c_x - \gamma(c_x - b_x) \quad (2)$$

$$v_x = a_x - \gamma(b_x - a_x) \quad (3)$$

$\varepsilon$ is adopted to address the decision makers' optimistic level and to create a judgment balance among the expert group.

The $\gamma$ generally ranges from 0 to 1 founded on if perceptions from experts are positive or negative. To express $\gamma$ under the common condition, this study uses 0.5.

Finally, the threshold $\sigma$ is calculated to validate more necessary indicators.

$\sigma = \sum_{x=1}^{n}(E_x/n)$ (n: the number of indicator) (4)

- *If $E_x \geq \sigma$, indicator $x$ is accepted.*
- *If $E_x < \sigma$, indicator $x$ is eliminated.*

## 3. Results

The results of data collection, network analysis, co-word analysis and the FDM analysis are revealed in this part.

### 3.1. Bibliometric

3.1.1. Network Analysis Results

In the data collection process, 436 articles and reviews were approached. The result from VOSviewer shows that 48 keywords appeared at least three times, and their distribution is displayed through bibliographic framework.

Figure 2 indicates that I4.0, IoTs, artificial intelligence (AI), cloud computing, virtual reality, and sustainable manufacturing had the highest frequency occurrences. These nodes are in the central places, which connect with other indicators. Sustainable industrial and operation engineering term has not yet been clarified in the literature. Indeed, this concept is the combination of small nodes in the network, such as engineering education, software engineering, and smart manufacturing. Indicators include I4.0, sustainable manufacturing, digital transformation, digitalization, and deep learning at the yellow points represent the latest considered subjects since 2019.

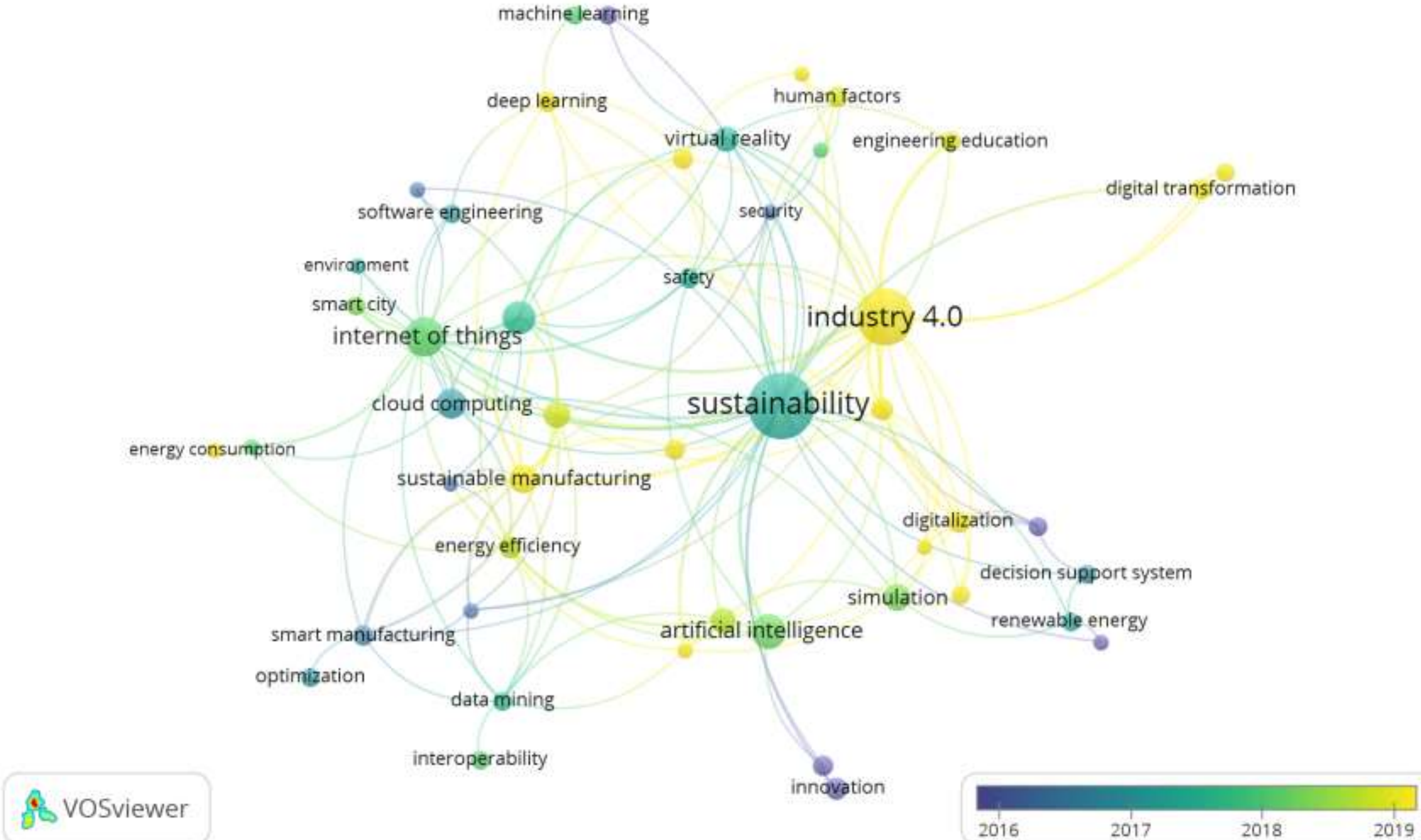



Figure 2. Co-occurrence of author keywords by publication year

3.1.2. Co-word analysis

In total, 48 keywords are withdrawn from the databases and formed in eight groups of clusters. Figure 3 presents a dataset of indicators and the relationship structure in a conceptual network.

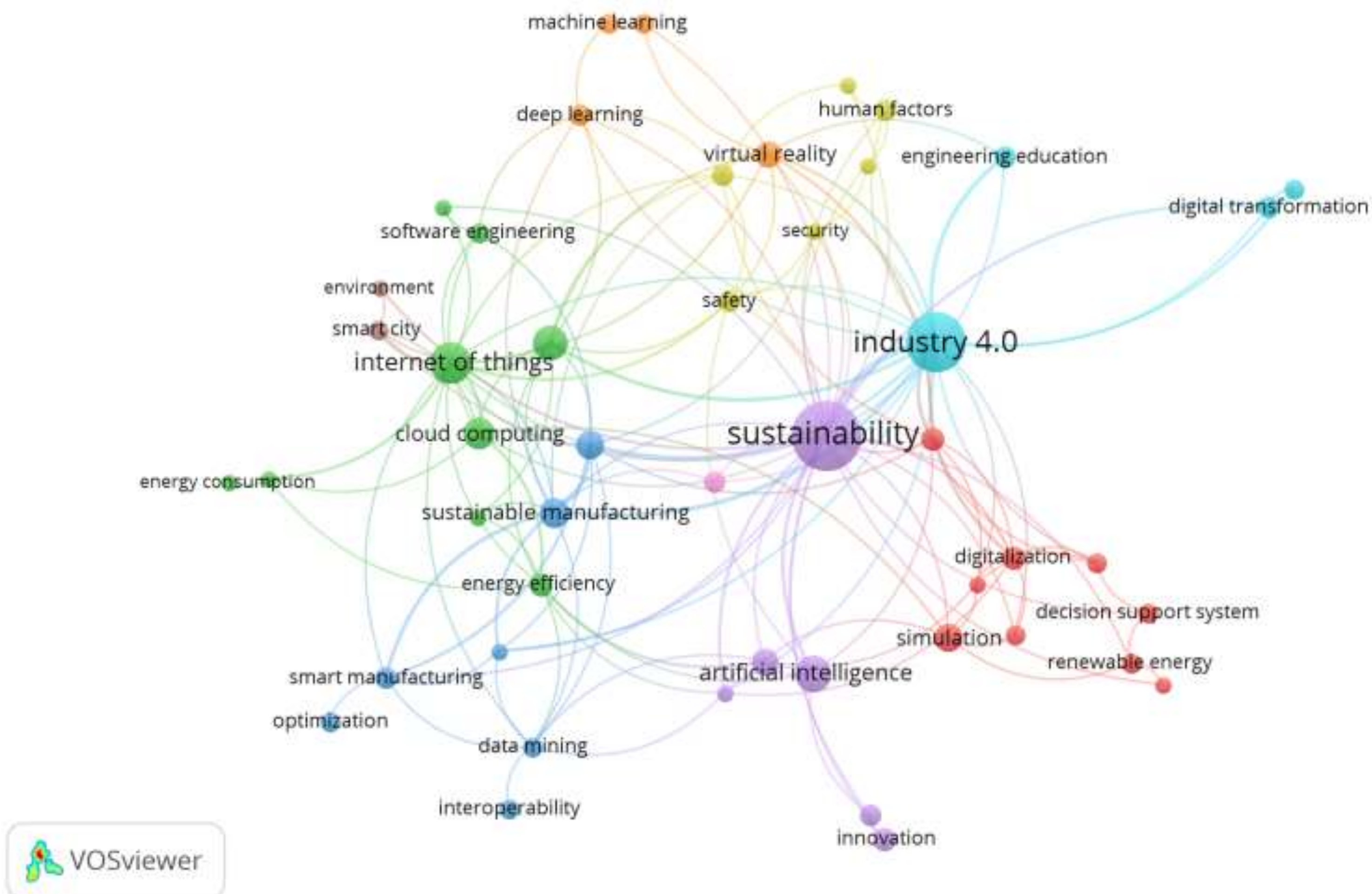



Figure 3. Co-occurrence of author keywords by clusters

The detailed labeling of eight clusters is conducted in Table 2. Cluster 1 is labeled lean manufacturing in I4.0. This cluster explores the innovation in manufacturing towards sustainability, covering decision support systems, digitalization, renewable energy and simulation. Cluster 2 promotes big data-driven and smart communication which is attributable to innovative technologies like IoTs, cloud computing, and software engineering. This cluster also pays attention to energy consumption and energy efficiency, which finally leads to sustainable manufacturing. Cluster 3 goes deeper in this area by focusing on data mining, interoperability, optimization, smart manufacturing, and sustainable manufacturing. This cluster clarifies the cyber-physical production system (CPPS) in industrial engineering. Cluster 4 turns back to the safety and security issues occurring throughout the digital transformation. Human factors are also reflected in this cluster since this process requires the coordination between human and modern machines. Cluster 5 introduces another new I4.0 technique aimed at innovation and sustainability and named AI for sustainability. This cluster presents an important smart manufacturing method for improving process safety and automatic management. Cluster 6 emphasizes the circular economy (CE) in a digital environment by concentrating on digital transformation, engineering education and I4.0 topics. Cluster 7 illustrates the learning process needed for digitalization through deep learning, machine learning, and virtual reality. This cluster considers business intelligence and virtual reality. Finally, cluster 8 concerns environmental sustainability, mentioning smart cities and the technological environment. This cluster provides a platform to support sustainable industrial and operational engineering.

Table 2. Co-occurrence of author keywords

| ID | Keyword | Cluster | Occurrence | Average published year |
|---|---|---|---|---|
| 1 | decision support system | | 4 | 2016.75 |
| 2 | design | | 4 | 2016 |
| 3 | digitalization | | 6 | 2019 |
| 4 | efficiency | | 3 | 2016 |
| 5 | integration | lean manufacturing in industry 4.0 | 3 | 2019 |
| 6 | lean | | 4 | 2019 |
| 7 | manufacturing | | 6 | 2019.167 |
| 8 | renewable energy | | 4 | 2017.25 |
| 9 | simulation | | 8 | 2018.25 |
| 10 | big data | big data driven and | 12 | 2017.583 |

| | | | | |
|---|---|---|---|---|
| 11 | cloud computing | smart communication | 10 | 2016.9 |
| 12 | energy consumption | | 3 | 2019.667 |
| 13 | energy efficiency | | 6 | 2018.667 |
| 14 | green manufacturing | | 3 | 2016.333 |
| 15 | information technology | | 3 | 2016.333 |
| 16 | internet of things | | 18 | 2018.056 |
| 17 | software engineering | | 4 | 2017 |
| 18 | wireless communication | | 3 | 2018 |
| 19 | cyber-physical systems | | 8 | 2018.75 |
| 20 | data mining | | 4 | 2017.5 |
| 21 | interoperability | | 4 | 2018 |
| 22 | optimization | cyber-physical production system | 4 | 2017 |
| 23 | product life cycle | | 3 | 2016.333 |
| 24 | smart manufacturing | | 5 | 2016.6 |
| 25 | sustainable manufacturing | | 9 | 2019.111 |
| 26 | digital twin | | 5 | 2020 |
| 27 | human factors | | 5 | 2018.8 |
| 28 | maintenance | | 3 | 2019.667 |
| 29 | safety | safety and security | 5 | 2017.4 |
| 30 | security | | 3 | 2016.333 |
| 31 | systems engineering | | 3 | 2018 |
| 32 | blockchain | | 5 | 2019.6 |
| 33 | education | | 5 | 2015.2 |

| | | | | |
|---|---|---|---|---|
| 34 | building information modelling | | 7 | 2018.571 |
| 35 | artificial intelligence | artificial intelligence for sustainability | 13 | 2018.154 |
| 36 | skills | | 3 | 2019.333 |
| 37 | innovation | | 6 | 2015.833 |
| 38 | sustainability | | 48 | 2017.313 |
| 39 | circular economy | | 4 | 2019.25 |
| 40 | engineering education | circular economy in digital environment | 5 | 2018.8 |
| 41 | digital transformation | | 5 | 2019.2 |
| 42 | industry 4.0 | | 35 | 2019.457 |
| 43 | deep learning | | 5 | 2019.6 |
| 44 | remote sensing | business intelligence and virtual reality | 4 | 2012.75 |
| 45 | machine learning | | 4 | 2018 |
| 46 | virtual reality | | 7 | 2017.429 |
| 47 | environment | environmental sustainability | 3 | 2017.333 |
| 48 | smart city | | 4 | 2018.25 |

The results reveal that topics related to these clusters were all researched in recent years, including indicators that are studied quite a great deal and others that have just begun to popularize. Concerning Table 2, the higher weight and average published year reveal that there are newer indicators, such as the following:  digitalization, integration, and lean manufacturing from cluster 1; energy consumption from cluster 2; sustainable manufacturing from cluster 3; digital twin, maintenance, and blockchain from cluster 4; skills in cluster 5; CE, digital transformation, and I4.0 in cluster 6; and deep learning in cluster 7. The latest cluster is CE in a digital environment, revealing the currently considered studies that need more attention.

### 3.3. FDM results

From the bibliometric analysis and co-word analysis, 48 keywords are proposed for evaluation based on the experts' judgments. The FDM process for the original set of indicators is explained in Table 3 by using equations (1)-(4).

Table 3. FDM screening out for indicators

| Indicators | l | u | D | Decision |
|---|---|---|---|---|
| decision support system | -0.036 | 0.911 | 0.691 | Accepted |
| design | -0.256 | 0.756 | 0.504 | Unaccepted |
| digitalization | 0.329 | 0.921 | 0.780 | Accepted |
| efficiency | -0.004 | 0.879 | 0.670 | Accepted |
| integration | 0.038 | 0.837 | 0.641 | Accepted |
| lean | -0.036 | 0.911 | 0.691 | Accepted |
| manufacturing | -0.273 | 0.773 | 0.516 | Unaccepted |
| renewable energy | 0.000 | 0.500 | 0.333 | Unaccepted |
| simulation | 0.000 | 0.500 | 0.333 | Unaccepted |
| big data | -0.055 | 0.930 | 0.704 | Accepted |
| cloud computing | 0.021 | 0.854 | 0.652 | Accepted |
| energy consumption | -0.284 | 0.784 | 0.523 | Unaccepted |
| energy efficiency | -0.084 | 0.959 | 0.723 | Accepted |
| green manufacturing | 0.000 | 0.500 | 0.333 | Unaccepted |
| information technology | 0.005 | 0.870 | 0.664 | Accepted |
| internet of things | 0.296 | 0.954 | 0.803 | Accepted |
| software engineering | -0.370 | 0.870 | 0.580 | Unaccepted |
| wireless communication | -0.031 | 0.906 | 0.688 | Accepted |
| cyber-physical systems | -0.039 | 0.914 | 0.693 | Accepted |
| data mining | -0.392 | 0.892 | 0.595 | Unaccepted |
| interoperability | -0.403 | 0.903 | 0.602 | Unaccepted |
| optimization | 0.337 | 0.913 | 0.775 | Accepted |

| | | | | |
|---|---|---|---|---|
| product life cycle | -0.281 | 0.781 | 0.520 | Unaccepted |
| smart manufacturing | -0.042 | 0.917 | 0.695 | Accepted |
| sustainable manufacturing | 0.017 | 0.858 | 0.655 | Accepted |
| digital twin | -0.325 | 0.825 | 0.550 | Unaccepted |
| human factors | 0.055 | 0.820 | 0.630 | Accepted |
| maintenance | -0.254 | 0.754 | 0.503 | Unaccepted |
| safety | -0.102 | 0.977 | 0.735 | Accepted |
| security | -0.093 | 0.968 | 0.729 | Accepted |
| systems engineering | -0.329 | 0.829 | 0.552 | Unaccepted |
| blockchain | -0.093 | 0.968 | 0.729 | Accepted |
| education | -0.316 | 0.816 | 0.544 | Unaccepted |
| building information modelling | 0.000 | 0.500 | 0.333 | Unaccepted |
| artificial intelligence | -0.042 | 0.917 | 0.695 | Accepted |
| skills | -0.273 | 0.773 | 0.516 | Unaccepted |
| innovation | -0.076 | 0.951 | 0.717 | Accepted |
| sustainability | -0.067 | 0.942 | 0.711 | Accepted |
| circular economy | -0.084 | 0.959 | 0.723 | Accepted |
| engineering education | 0.000 | 0.500 | 0.333 | Unaccepted |
| digital transformation | -0.067 | 0.942 | 0.711 | Accepted |
| industry 4.0 | -0.067 | 0.942 | 0.711 | Accepted |
| deep learning | -0.055 | 0.930 | 0.704 | Accepted |
| remote sensing | 0.000 | 0.500 | 0.333 | Unaccepted |
| machine learning | -0.020 | 0.895 | 0.680 | Accepted |
| virtual reality | -0.093 | 0.968 | 0.729 | Accepted |

| | | | | |
|---|---|---|---|---|
| environment | -0.047 | 0.922 | 0.698 | Accepted |
| smart city | -0.072 | 0.947 | 0.715 | Accepted |
| | Threshold | | **0.618** | |

Table 4 illustrates 30 critical indicators belonging to 8 clusters with values over the threshold of 0.618. These clusters include the following: lean manufacturing in I4.0; big data driven and smart communication; CPPS; safety and security; AI for sustainability; CE in a digital environment; business intelligence and virtual reality; and environmental sustainability.

Table 4. FDM result for indicators and clusters

| Indicator | | Cluster |
|---|---|---|
| I1 | decision support system | lean manufacturing in industry 4.0 |
| I2 | digitalization | |
| I3 | efficiency | |
| I4 | integration | |
| I5 | lean | |
| I6 | big data | big data driven and smart communication |
| I7 | cloud computing | |
| I8 | energy efficiency | |
| I9 | information technology | |
| I10 | internet of things | |
| I11 | wireless communication | |
| I12 | cyber-physical systems | cyber-physical production system |
| I13 | optimization | |
| I14 | smart manufacturing | |
| I15 | sustainable manufacturing | |
| I16 | human factors | safety and security |

| | | |
|---|---|---|
| I17 | safety | |
| I18 | security | |
| I19 | blockchain | |
| I20 | artificial intelligence | |
| I21 | innovation | artificial intelligence for sustainability |
| I22 | sustainability | |
| I23 | circular economy | |
| I24 | digital transformation | circular economy in digital environment |
| I25 | industry 4.0 | |
| I26 | deep learning | |
| I27 | machine learning | business intelligence and virtual reality |
| I28 | virtual reality | |
| I29 | environment | environmental sustainability |
| I30 | smart city | |

## 4. Discussion and implications

This section discusses eight study fields comprising the following: lean manufacturing in I4.0; big data driven and smart communication; CPPSs; safety and security; AI for sustainability; CE in a digital environment; business intelligence and virtual reality; and environmental sustainability.

### 4.1. Lean manufacturing in Industry 4.0

Lean manufacturing has the major aim of identifying and eliminating waste in time, money and other resources by recognizing any unneeded activities, simplifying the process, and establishing standardized routines (Buer et al., 2018; Sony and Naik, 2020). Lean manufacturing execution's center is full engagement of all internal along with external stakeholders in order to get success. The concept offers a firm-wide approach that enhances reliability and flexibility while decreasing lead times and inventory carrying costs; in addition, it enables firms to attain a competitive edge by utilizing resources, cutting costs, boosting productivity and quality, expanding efficiency, profitability, efficacy (Tseng et al., 2020).

As a necessary basis for I4.0 execution, lean manufacturing is employed since the streamlined and waste-free process and standardized procedure attained throughout a lean transformation eases future attempts to automatize and digitalize the manufacturing process (Buer et al., 2018). However, the synergy between the two mechanisms needs to be taken into consideration to aim at operational excellence, as I4.0 targets accelerate information flows and lean manufacturing concentrates on waste elimination to promote physical flows. Optimistic synergistic association between advanced production technologies and lean disciplines in anticipating operational achievement regarding expense, lead period, product quality, flexibility is supported. By the interactions between information technologies with lean practices, reciprocacity between production technologies and lean procedures is shaped and manipulated (Khanchanapong et al., 2014). Thus, the value to customers is added, and resources are optimally utilized in the interest of combination of lean manufacturing with I4.0 application, resulting in greatly responsive synthesis and creating value-added streams in the most efficient way (Sony and Naik, 2020).

Lean manufacturing is an achievable approach for firm endurance in I4.0. Prior studies have focused on how I4.0 is related to lean manufacturing together with its effects on firm accomplishment. Despite high costs together with challenges in its implementation, lean digitization, characterized as the integration of lean manufacturing and digitalization, eventually gives firms better competitiveness (Ghobakhloo and Fathi, 2020). For example, lean manufacturing practices are affiliated with I4.0 technologies positively with simultaneous application resulting in greater performance improvements (Tortorella and Fettermann, 2019). I4.0 technologies moderate lean manufacturing impact on operational attainment enhancement in contrasting paths. In particular, technologies pertaining to product or service moderate influence concerning flow operations on achievement positively while process-pertained technologies moderate influence of low-setup operations on achievement negatively. When lean manufacturing disciplines are widely executed in the firm, it is easier to adopt higher levels of I4.0. However, the firms' readiness to apply contemporary technologies is lower in case procedures are not strongly devised and consecutive enhancement practices are not set up. Furthermore, both factory digitalization and lean manufacturing possess restricted capability for separately creating a competitive edge. Enabling impact of lean manufacturing on I4.0 as well as I4.0 empowering effect on lean manufacturing are investigated with a thoroughly pairwise investigation at level of practice-technology. A reality demonstration of cloud computing in the I4.0 technology and a main lean measure (Kanban) integration introduces a cloud-founded Kanban decision support system (Shahin et al., 2020).

Nevertheless, inspecting promising attainment implications are indispensable to assess I4.0 and lean manufacturing synthesis in further empirical studies. Key issues are the evaluation of the rewards brought about by incorporating lean manufacturing and I4.0, a comparison relating to performance effects of pure I4.0 or lean manufacturing to examine whether a favored implementation order of the two mechanisms is needed (Buer et al., 2018). Enablers of vertical integration founded on lean manufacturing, algorithms relating to end-to-end engineering consolidation and lean manufacturing, drivers relating to horizontal integration, should be thoroughly analyzed in future studies (Sony and Naik, 2020). Together with studies verifying the extent to which I4.0 technologies strengthen lean principles implementation and the firms' productivity, recommending I4.0 technologies' modern applications to additionally promote such principles at three levels such as control, optimization, autonomy is necessitated (Rosin et al., 2020). Moreover, moderator role of I4.0 technologies in exploring lean manufacturing's influence on the sustainable achievement of firms should be also noted (Kamble et al., 2020).

### 4.2. Big data driven and smart communication

The requirement for enhancing sustainable performance pushes the firms to explore operational data-driven approaches as well as optimized communication methodology (Kamble et al., 2021). Under the I4.0 background of supporting sustainable development, the amount of various data resources obtained through the IoT is increasing the magnitude of big data along with new communication technologies (Ma et al., 2020). Big data-driven communication refers to a communicating approach based on a great volume of data including all structured and unstructured information with high quantity, speed, diversity and veracity, which is generated and collected with speedy processing (Majeed et al., 2021).

Huge attention has been placed on big data technology during the explosive growth of information in I4.0; however, how to apply this technique in the manufacturing area is only in the beginning stage (Wang et al., 2020). There are different opinions on the nature of an organization's operations, and big data analytics have been proven to potentially assist in transforming and advancing manufacturing and service systems by helping firms make intelligent decisions related to production and management (Srinivasan et al., 2019). I4.0 technologies have become the encouragement for building competitive advantages with outstanding applications like big data analytics or IoT (Kamble et al., 2021). Big data technique for information storing, examining and communicating are emphasized to establish actionable awareness for firms and governmental agencies (Srinivasan et al., 2019). Indeed, the efficient operating of big data is essential to strongly connect with cloud computing technology for better large-scale information researching and analyzing (Zhou and Zhao, 2020). Cloud computing supports the fundamental layer for big data sources and offers necessary data for IoT devices; in adverse, big data supplies application platforms to promote cloud computing (Hajjaji et al., 2021). Since the big data collection through appropriate, timely, and consistent process is imperative for enforcing new CE models, there is a recent need for studies on the collaboration among this concept and circular framework designs (Rosa et al., 2020; Kamble et al., 2021).

The significance of communication studies is necessary towards smart manufacturing, as it brings advantages to various domains by facilitating the adoption of communication technologies, such as those technologies meeting the different requirements of applications, and support the achievement of long-term operational strategies. As an efficient and reliable communication protocol, smart communications also sustain coverage and lower power consumption to better satisfy customers and react to changes in marketplace (Oztemel and Gursev, 2020). For example, the wireless sensor network is seen as a common communication application which provides large coverage and consume a low power level (Lau et al., 2019). However, prior studies were only concerned with defining the conditions of adopting highly technological methods to improve existing approaches, but did not propose solutions to deal with current barriers. Despite certain solutions have been provided, modern productions with smart machines are not enough to comprehensively promote all the expected I4.0 benefits, and there is still a need to enable the generation of new powerful smart communication networks.

Big data-driven and smart communication in a supply chain is argued to help to increase economic benefits, such as cost savings, a strengthening of coordination and a faster adapting to market demands (Tseng et al., 2019). While IoT is acknowledged to facilitate the reliable transfer of information between "things and processes", the combination between IoTs and big data-driven approaches acts as an important resource for firms to operate remanufacturing and recycling processes (Wang et al., 2020; Bag et al., 2021). Smart communications generate an efficient interacting system that ensures instant action and smooth information exchange. Since smart communication enhances the collaboration among all stakeholders through information sharing and communication, it highlights the capability of facilitating CE manufacturing in firms (Kamble et al., 2021). Applying the IoT and big data technology to manufacturing area creates an "Internet of manufacturing things" context, in which various data of resource and energy are accessible for production planning, thus improving sustainable industrial and operational efficiency (Ma et al., 2020). As IoT devices and the expectations towards smart systems increase, communication issues between machines inevitably emerge; however, the solutions for these issues are still lacking and call for further studies.

### 4.3. Cyber-physical production system

Traditional production systems are experiencing a digital transformation. In this context, CPS is a fundamental element of I4.0 exertion, since in the appropriate systems, the concept merges imaging and control functionalities, with the key characteristics of reacting to any feedback created, favoring the immediate control and analysis of process feedback to achieve the anticipated outputs (Oztemel and Gursev, 2020). The CPS application in manufacturing environments leads to the term CPPS in which cyber and physical objects are unified as well as governed by manufacturing implementation systems together with informational schemes with an aim to attaining energetic and adaptable manufacturing featured by intelligence, responsiveness, connectivity, to internal together with external alterations (Okpoti and Jeong, 2021). Full manufacturing process components, such as equipment, produces, procedure, systems, persons are connected in an informative environment by integrating real and virtual production, which could have a thorough effect on a firm's strategic, tactical, and operational decisions.

Because of the need to comply with the vigorously changing production environment and to adopt to external disruptions and an unstable market demand, smart manufacturing has turned into an unavoidable tendency in I4.0, actualizing synergy between cyber and physical has also become necessary (Tao et al., 2019). CPSs provide an indispensable technological basis to promote smart manufacturing by linking virtual and real environments (Ying et al., 2021). Currently, facing an increasing need for sustainability awareness and rising environmental pressure, firms are greatly attempting to focus on matters relating to sustainability without giving up the consumers' demands and market competitive ability. In such situations, smart manufacturing provides a competitive advantage for firms and makes the industry more efficient and sustainable by enhancing productivity, quality, flexibility and the ability to attain customized products at a wide-ranging scale with improved resource use.

Obviously, CPPSs are crucial to future manufacturing systems. To realize this anticipation, further study and development together with information technology activities are needed, and socio-ethical facets of CPSs together with CPPSs must also be comprehensively examined. I4.0 led by intelligent devices and smart manufacturing is capable of diminishing manufacturing waste, overproduction and energy consumption. Hence, more studies showing how waste may be cut down are necessary. In addition, fostering schemes to integrate smart manufacturing networks in such a manner that they prosper by shared resources, such as natural materials, power plants, the labor force should be concentrated in future studies. Furthermore, the contribution of I4.0 to more sustainable manufacturing value generation in the extant literature is mostly related to economically and environmentally sustainability pillars. I4.0 has an immense ability to actualize sustainable manufacturing value generation in social pillar (Kamble et al., 2020). Investigating chances for improving sustainability in varied degrees by using I4.0 technologies is till restricted and as a result, examining the I4.0 technology influences on various criteria regarding sustainability at product, procedure, system level is limited in extant literature (Enyoghasi and Badurdeen, 2021).

### 4.4. Safety and security

Safety and security in I4.0 are defined as the secure interaction between independent systems and humans and the avoidance of the interference of digital networks that create damage and an interruption of procedures, including and up to the destruction of manufacturing systems (Weber et al., 2019). In the process of implementing I4.0 with highly independent and collaborative components, the management of complex infrastructure to ensure safety and security factors is required (Oztemel and Gursev, 2020). The academic and empirical study efforts, along with production innovation, all aim to create smart factories which support cost-effective, sustainable, safe and secure manufacturing systems (Tuptuk and Hailes, 2018). The integration with I4.0 capabilities empowers a safe and secure environment that encourages more ethical and moral behaviors that can increase sustainability through mutual cooperation.

Focusing on a smart system design under development or demonstrating a failure effect model for investigating cause and effect, prior studies have analyzed safety and security as issues. For example, the safety aspect is emphasized to protect the system from unexpected faults, whereas the security aspect includes protection from both foreseen and unforeseen hazards throughout the application of cyber-physical system (Kavallieratos et al., 2020). Security issue is considered as a secondary matter rather than a vital element of deployment operation, while the existing industrial and manufacturing systems are easily vulnerable to cyber-based attacks in poorly trained and prepared firms (Tuptuk and Hailes, 2018). Further, there is a shortcoming in reporting this aspect as a key driver of further implementation of I4.0 and digitalization procedures, although the indicators of safety and security are still being developed to improve process performance (Lee et al., 2019). A recurring obstacle of the existing studies on the joint security and safety concerns that need to be overcome is that these studies do not identify conflicts and largely neglect the examination of the fulfilment of distinct security objectives (Kavallieratos et al., 2020).

The increasing number of cyber-attacks is a main challenge to I4.0 implementation, and applying advanced technology devices without caring of safety and security makes the industrial engineering among the highest vulnerable industries, highlighting the need for more secure and reliable frameworks for machines and operators in industrial manufacturing systems. Safety and security in networks are necessary because they help to prevent employees from dangerous situations when working in manufacturing industry (Khalid et al., 2018). The consideration of safety and security is seen as a continuing procedure starting at or before designing step, and the occurrence of new barriers requires a basic evaluation of the entire plant's security (Tuptuk and Hailes, 2018). Although IoTs provide firms with insight of the way their systems truly operate throughout the entirety of procedures, the study on safety and security issues related to IoT programs concluded that in complicated platforms with multi data flows, most approaches lacked a consideration of security issues (Ogonji et al., 2020). As one of core I4.0 technologies, blockchain has been adopted to guarantee security and solve numerous traditional threats by creating attack-resistant and digital data storage and by providing a sharing platform that employs linked block structures to verify and synchronize data (Bhushan et al., 2020).

Furthermore, the human factors of safety and security also need examination because humans can be harmed by inaccurate operation systems, or severe injuries can occur during the interaction process with autonomous systems (Weber et al., 2019). Studies researching human factor application generally find that both the human outcomes and the system benefits gained are considerably greater. While safety issues and security issues are argued to be key factors in the development of modern systems, the failure to adequately address human factor issues in working environment also causes serious risks in operationalization procedures; nonetheless, there is still lack of studies on this topic when researching I4.0 area (Neumann et al., 2021). Further, in I4.0 transition, whereas studies on the machine-centered manufacturing industry highlighted the smart factory concept of the future as digitized and comprising automated systems, human factors and their well-being were neglected; thus, need further attention (Kadir and Broberg, 2021).

### 4.5. Artificial intelligence for sustainability

AI is usually connected to the concept of data analysis, machine learning, and refers to human-like intelligent programmed systems; thus, AI for sustainability is acknowledged as a group of computational and statistical devices that help computers implement sustainable goals normally done by human intelligence (Liu et al., 2020). Since AI appearance promotes knowledge creation, this technology is believed to significantly increase economic tenet, one objective of sustainable development. In the I4.0 revolution, AI development is focused on innovative, green, and mutual factors to enhance smart manufacturing (Mao et al., 2019). AI applications offer three major advantages: (1) permitting the imperative but repeated and waste-of-time works to be done automatically; (2) disclosing essential and critical information among big amounts of unstructured data which people once have to handle by themself; and (3) addressing the most complicated issues by integrating various systems and data resources (Nishant et al., 2020). Furthermore, AI systems enable natural language processing to ease communication, store information, automate reasoning, and facilitate machine learning to comply with different business environment (Loureiro et al., 2020).

Prior studies have applied AI experiments for theoretical processes as well as realistic solutions (Goralski and Tan, 2020). Although AI is not a new academic field of study, it has only recently been acknowledged for a set of applications in technological developments. AI applications are an attention field of study involving computational intelligent techniques used to design and manufacture products in traditional sectors (Jimeno-Morenilla et al., 2021). For example, studies on AI for sustainability mainly focused on machine learning techniques and algorithms in order to present the way devices examine and gain knowledge from collected information (Nishant et al., 2020). In fashion industry, AI is adopted to deal with difficult problems in all manufacturing process stages, which then could be completed in a shorter time under AI than under the traditional approach. Studies in chemistry manufacturing show the AI function in greater and quicker synthesizing new organic compounds to produce medicament drugs (Lenoir et al., 2020). However, the potential of disruptive AI technology to enhance sustainable manufacturing is still shortcoming. Although AI has a positive effect on sustainability goals through technological innovations, studies on this issue are still lacking (Liu et al., 2020). Thus, there is a need for robust study methodology to evaluate AI's longstanding impact and address the privacy issues resulting from AI application.

In the I4.0 era, AI is seen as one of the most progressive techniques that will have remarkable effects in several fields, and the support of big data has enhanced AI power as well (Duan et al., 2019). Big data is capable of changing the approach firms use to handle conventional supply networks, whereas AI enables a system to collect and achieve knowledge from various data sources to further accomplish specific tasks; thus, big data and AI integration enhances sustainability opportunities throughout production area (Bag et al., 2021). This concept is considered not only an internal technological innovation but also an external cause that promotes other innovations and is therefore critical for manufacturing firms to maintain stability (Liu et al., 2020). AI is argued to be critical for smart manufacturing through the improvement of safety control and efficiency in consuming materials and energy (Mao et al., 2019). Further, AI applications also assist manufacturing systems in predicting long-term demands and deciding production quantity every day to decrease unnecessary operations (Frank et al., 2019). AI positively affects manufacturing in low-income countries since it offers new opportunities to break the cycle of poverty; however, in advanced countries, it is considered negatively due to the fear of job loss (Ahmad et al., 2021). Consequently, whereas AI is a potential motivation for sustainability improvement, the adoption of this technology still creates unwanted results that require deep study to find solutions.

### 4.6. Circular economy in a digital environment

Since a high level of competition in business requires firms to change their manufacturing process, one of the best ways to utilize resources is by applying CE practices within operations (Rosa et al., 2020). While current system links with the linear perspective enduring industrial manufacture, CE is seen as a more sustainable model and an appropriate selection to take place of the linear model, in which resources are circulated (Sarja et al., 2021). CE in a digital environment is considered as a method applying emerging innovative technologies to recover usable material from used products and redistribute them in the production line (Chauhan et al., 2021). The benefits of this concept consist of decreasing environmental effects, boosting financial performance, adopting recycled and recovered resources to lessen sustainability pressure through an overall system change. While CE is argued to support the circularity in manufacturing processes, I4.0 is presented as a digital environment that enhances CE development. Nonetheless, promoting I4.0 technologies to manage the operational process is still vulnerable since it is complicated to define valid measurement and elements' interrelationship to comprise this process (Bui et al., 2020). Thus, a multidisciplinary approach is urgent to improve sustainable performance by combining I4.0 and CE.

Although there are firm links between CE and sustainability, there is still theoretical and practical uncertainty regarding its principles (Sarja et al., 2021). Innovation business models are implied to enable firms adapting to CE principles; yet, available analysis on how to strategically implement and systematically understand organizational obstacles and the catalyst for CE-related changes is still lacking (Centobelli et al., 2020). Furthermore, there is also an emphasis on the significance of CE and emerging technologies such as I4.0, which promote efficient waste in smart cities; nevertheless, lack of studies considered CE in I4.0 with smart waste management (Chauhan et al., 2021). In addition, the advantage of digitalization on CE enhancement is comparatively untouched, despite CE is on the rise, and I4.0 is acknowledged as the most imperative attribute in digitalizing procedure (Bag et al., 2021).

Firms need to transform to remain competitive since I4.0 has driven a wave of technologies that lead to the digitization and simplification in business (Bag et al., 2021). Digital transformation or digitization through innovative technologies shared between the physical and real environment has supported firms to achieve competitive advantage and differentiate a firm from competitors. The significant digital transformations in I4.0 are argued to result in numerous advantages (Ghobakhloo, 2020). For example, digitization enables a fully digital CE accomplishment through higher transparency of process centralization and requires firms to improve key indicators of flexibility, efficiency, productivity, and quality and to establish critical security measures (Dutta et al., 2020). However, in the CE transition process, the study of firms changing from the old industrial styles to inter-connected enterprises in I4.0 era is neglected (Frank et al., 2019). Further, the implications of this process for the firm's capacity and innovative performance are also not clear and need to be exploited in the future (Fernández-Rovira et al., 2021). It is essential for a well-understood digitization standard, and each stage of this process needs to be clarified and proceeded.

I4.0-based techniques have been revealed to develop smart manufacture for CE, as it declares a revolution related to a novel function on how to collaborate production and digitalized progress to maximize output with minimum materials (Sony and Naik, 2019; Bag et al., 2021). Although new technology transformations create challenges to I4.0 implementation, they still guide firms to achieve lasting competitiveness and adaptation to changes of operating environment. However, implementing CE in I4.0 requires the development of different and more specialized skills (Sony and Naik, 2020). Nevertheless, from such a perspective and in the context of the attention to human factors and ergonomics, a study of this topic characterized as a sociotechnical system that contains both social and technical aspects is still missing.

### 4.7. Business intelligence and virtual reality

As the business environment becomes more competitive and the information advantage increases, business intelligence, which applies data analytics techniques to create decisive information to support and optimize decision-making, contributes to strategic planning process of a firm. Business intelligence is considered an effective solution that provides a valuable tool and fundamental approach to increase a firm’s value by facilitating the understanding of a firm’s information assets, including customer and supply chain data, manufacturing, sales, marketing information and other operational data sources, allowing firms to integrate a consistent framework for real-time reporting combined with a detailed analysis (Chen and Lin, 2020). The concept enables firms to actively sense changing business circumstances and transform business processes for optimal resource allocation and utilization, which drives the firms’ operations to achieve profitability and competitiveness.

I4.0 involves the digital transformation of production processes via incorporating production systems, appliances along with data analytics for facilitating the ability of manufacturing machines to make choices founded on provided data together with machine learning algorithms (Papananias et al., 2020). Particularly, machine learning emphasizing the principles that form an algorithm can grasp and forecast the consequence by identifying an underlying archetype in input information and by generating logical associations through employing statistical method (Injadat et al., 2021). As a potential answer to contemporary manufacturing system challenges, such as growing complexity, dynamic, high dimensionality, and disorganized structures, machine learning's advantages and disadvantages from a manufacturing perspective are discussed. Machine learning methods are an encouraging approach favoring the manufacturing industry concerning the entire operations and processes (Sharp et al., 2018). For manufacturing systems, the execution of a machine learning algorithm enables a machine or other gadget to grasp its baseline along with working states spontaneously and can generate and promote a knowledge base during production process (Chen, 2020). Machine learning is also employed in many aspects of additive manufacturing to enhance the whole design and manufacturing workflow (Goh et al., 2020).

Deep learning, as an advance in AI, presents distinguished performance for many applications, like speech recognition, natural language processing, and image replication; it comprises a group of machine learning techniques that apply artificial recurrent neural networks with a more complicated architecture grasping complex features by connecting the data and computationally efficient training algorithms (Lin et al., 2020). Production is converted into greatly optimal smart facilities offering advantages in terms of decreasing operating expenses, matching with unstable customer need, enhancing capacity, attaining better visibility, diminishing spare time, obtaining more operations' value for international competition by virtue of breakthrough analytics supported by deep learning. Moreover, by enabling the transformation of the unprecedented data amount into actionable and intelligent information, this concept also provides contemporary visibility into operations together with real-time attainment means as well as costs for decision-makers (Wang et al., 2018).

Virtual reality as a unique approach for connecting with the developing digital landscape is characterized as technologies' set that facilitate people not only to immersive sight beyond reality but also to hear, touch and even to communicate with virtual objects (Guo et al., 2020). Virtual reality tools are part of smart functionality in I4.0 relating to the employees' tasks, allowing them to become more energetic and responsive in order to follow requirements of manufacturing system (Frank et al., 2019). In business, technology is anticipated to be imperative because of its basic reimagination in the manners firms associate with consumers and improvement in the manufacturing process, product design, prototyping (de Regt et al., 2020). Furthermore, the integration of human-robot simulation with virtual reality assists in estimating cycle time, establishing process plans, layout optimization and developing robot control programs, making it a promising technology with a growing capability to make maximum sense of the capability of artificial reality in changing how humans perform activities (Malik et al., 2019).

However, strategies addressing challenges connecting to human resource such as exercising safety situations, training technical processes along with skills, reconstructing how human resources obtain modern skills, boosting compassionate behaviors relating to customer service, easing employee hiring, remain unclear in the literature (de Regt et al., 2020). Further analysis on the application of business intelligence is needed to better understand how business intelligence enables firms to gain competitiveness in business operations. Future study should bring in more interesting findings in case more factors beyond the sense-transform-drive conceptual framework are taken into account (Chen and Lin, 2020). With data availability in each product life-cycle's phase and advancements relating to algorithms as well as software instruments, machine learning is a suitable, potential means for more lean, agile and energy-effective production schemes which requires more studies and applications with a more focus on life-cycle or firm-wide (Sharp et al., 2018). Further, more studies are needed on how to manage the overwhelming data connected with the manufacturing industry through the deep learning execution and deployment for applications in reality, such as smart manufacturing based on data considerations, model choice, generic model development, incremental studying, model imaginativeness (Wang et al., 2018). Despite the achievements in the literature, there is still a lack of a more profound analysis and advancement in industrial application scenarios, particularly in I4.0 (Guo et al., 2020).

### 4.8. Environmental sustainability

The conservation and viability of ecological system functions for the human base of life are characterized as environmental sustainability. This concept acknowledging the interplay between environmental effects and economic prosperity is essential viewpoint in the firms' decisions (Luo et al., 2021). Environmental sustainability in I4.0 has been examined in the literature. In particular, disruptive technologies enable the release of the full potential of environmental sustainability. Digital transformation initiated by I4.0 assists environmental sustainability by bettering resource efficiency together with increasing utilization in renewable energy (Beier et al., 2017). Information gathering and processing improvements enable better management of energy efficiency, the improvement of water quality, and the reduction via automatic production processes, in air pollution and heavy metals (Gobbo et al., 2018). Moreover, I4.0 technologies facilitate efficient resource allocation, decrease usage of resource, expand the usage of renewable together with recovering resources (Nara et al., 2021).

As information ecological mechanisms in which various institutions and industrial systems are highly integrated and automatically operate, smart cities also require an astute infrastructure to improve life quality accompanied by a sustainable environment for their inhabitants (Fu and Zhu, 2020). This need has resulted in the provision of technology platforms to support sustainable industrial and operation engineering by I4.0 as the core of the smart cities' applications, allowing for collecting information from various sources and the consequential data analysis as a means to cater context-founded optimum answers to peculiar problems (Abbate et al., 2019). To be specific, IoT buildings block for smart cities have the potential to capitalize on sustainable information and communication technologies to supervise and manage physical and information flows (Onu and Mbohwa, 2021). Municipalities, firms, and citizens can obtain, assess and handle data in real time for the purpose of making better choices based on a large IoT-based network (Cha et al., 2021). Firms derive more benefits by using advanced infrastructures, larger collaboration, networking, as smart city supports a greater proportion of innovation, coherence, and creativity.

Moreover, smart cities are acknowledged as an opportunity for cost reduction, a mechanism for the improvement of service quality and a method to attain a decrease in environmental effects during manufacturing processes (Nižetić et al., 2019). Lessening pollution while securing operations and non-restorable energies' sustainability, modern cities are giving attention to sources of renewable energy (Silva et al., 2018). Therefore, modern smart cities' primary concerns encompass maintaining the resources together with ecosystem by diminishing pollution and competently exploiting resources, reducing the environmental effects of manufacturing. However, policies that improve energy, environmental sustainability and technological innovation as the foundation for intensifying the smartness of cities are still lacking.

Overall, the I4.0 implications concerning environmental sustainability necessitate further examination. The enhanced quality of life and the rapidly increasing world population have given rise to an ever-growing raw materials and energy demand, conceivably restraining the efficiency effect of digitization. This scenario requires public policy and multilateral agreements to handle the unanticipated environmental sustainability effects of I4.0 (Ghobakhloo, 2020). Moreover, current methods for environmental sustainability evaluation, including the life cycle assessment, environmental track, the eco-efficiency index, that is used to instruct firms in environmental control and product determination, show certain limitations. In this context, future studies should concentrate on designing a multi-facet approach and a hybrid assessment scheme (Luo et al., 2021). The smart cities' potentiality relating to solving environmental dilemmas together with waste management should be explored with reference to investigating impacts regarding policy, rule, technology schemes, product planning strategies. A strong plan of action to design smart cities for strengthening comprehensive citizen engagement in framing, building and devoting smart city technologies is encouraged for further study.

## 5. Concluding remarks

Despite the importance of sustainable industrial and operation engineering in the firms' activities, this concept is still underdeveloped. Industrial and operational engineering is being promoted forward to sustainability; yet, the systematic knowledge that orients necessary practices is not completely developed. Since comprehensive understanding of the literature review is critical to solve the existing gap, this study is implemented to clarify the current status of sustainable industrial and operation engineering; then, give suggestion for next studies. In which, 436 publications are reviewed through VOSviewer. Totally, 48 keywords appear at least three times; among these keywords, I4.0, IoTs, AI, cloud computing, virtual reality, and sustainable manufacturing had the highest occurrences. FDM was adopted to arrange critical indicators into eight clusters: lean manufacturing in I4.0; big data driven and smart communication; CPPS; safety and security; AI for sustainability; CE in a digital environment; business intelligence and virtual reality; and environmental sustainability.

This study's contributions are providing bibliometric status concerning sustainable industrial and operation engineering towards I4.0; suggesting guidance for upcoming studies and realistic achievements. There are totally 48 keywords derived from the databases which were grouped into eight clusters such as lean manufacturing in I4.0; big data driven and smart communications; CPPS; safety and security; AI for sustainability; CE in a digital environment; business intelligence and virtual reality; and environmental sustainability. This study supports firms in making decisions on utilizing I4.0 technologies to achieve sustainable industrial and operational engineering. Furthermore, both professionals and practitioners can take advantage of these results for future examination and investigation in the field of industrial and operation engineering towards I4.0 linked with sustainability. Following are the gaps and directions for upcoming study.

- Further studies should pay attention to rewards from lean manufacturing and I4.0 integration, I4.0 technologies' latest applications to stimulate lean principles at control, optimization, and autonomy level. Validating the extent to which technologies consolidate the lean principles' employment and the firms' productivity is needed. Investigating technologies' moderator role in effect of lean manufacturing on the firms' sustainable achievement should also be explored further.

- Big data-driven and smart communications help generate an efficient interacting system, thus, improving sustainable industrial and operational efficiency. However, there is still a lack of studies on new powerful smart communication networks to enhance all the expected I4.0 goals. Moreover, the increasing communication issues between machines also call for further studies.
- Further study of the information technology activities, the socio-ethical features of CPSs together with CPPSs is needed. An examination of conceptual structures of incorporating smart manufacturing systems benefiting from shared resources is needed. The ability of I4.0 to create sustainable industrial merit generation in societal aspects is lacking. The indicators regarding product, process and system sustainability are still limited from the viewpoint of I4.0 technologies.
- Future studies on joint security and safety should pay attention to identifying conflicts and the fulfilment of security's distinct objectives. Process of engineering design and management frequently separates with human factor, although the failure to adequately address this factor can lead to serious problems in operationalization procedures; thus, further studies are needed.
- The topics related to AI for sustainability should focus on the effect of this technology on promoting sustainability-related manufacturing, along with robust study methods to examine the long-term effect and to ensure the consideration of the privacy issues in AI application data. In addition, the implementation of this technology in developed countries still leads to unwanted results that require studies to determine appropriate solutions.
- For CE in digital environments, more studies are required on multidisciplinary approaches to integrate CE and I4.0 with smart waste management. A good understanding of standard digitization obligations, the development of different and specialized skills, an attention to human factors and ergonomics, and a clear road map of CE implementation are suggested.
- Further examination of business intelligence utilization is needed on how business intelligence facilitates firms to attain competitiveness. This examination should include the machine learning adoption of a life-cycle or firm-wide center for capitalizing on increasing data magnitude. Adopting and using deep learning regarding data issues, model choice, generic model development, incremental studying, model imaginativeness is needed. Virtual reality and the ways in which it rearranges how human resources gain new skills require more thorough analysis. Increasing employee recruitment, practicing safety schemes, developing technical training procedures, and improving empathic behaviors in customer service to advance industrial application and human resource challenges are areas requiring urgent attention.
- A multi-facet approach and a hybrid environmental sustainability assessment plan, as well as public policy and multilateral agreements for managing the unpredictable environmental sustainability influences of I4.0, require further examination. The smart cities' potentiality in dealing with ecological matters and waste management needs to be investigated with a

consideration of the effects of policy, rule, technology arrangement, product planning strategies, and extensive citizen involvement.

There are some limitations for this study. First, the Scopus database was used in this study. Despite its broad scope, it also includes low impact sources. Therefore, future studies should employ other databases or incorporate different sources to enhance the generalizability of the results. Second, only articles and review papers were utilized in the review process; hence, to expand the data coverage, pertinent books along with book chapters should be embedded in future study. Third, the expert panel comprising only 15 members is able to induce analysis prejudice as a result of their understanding, practice, familiarity with the study area. To prevent such problems, increasing the number of respondents is recommended for future studies.

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**APPENDIX A. Respondents' demographic for FDM result**

| Expert | Position | Education levels | Years of experience | Organization type (academia/practice) | Major operation/research field |
|---|---|---|---|---|---|
| 1 | Manager | PhD | 20 | Practice | Electronics |
| 2 | Manager | Master | 23 | Practice | Food processing |
| 3 | Professional | Master | 10 | Practice | Electronics |
| 4 | Professional | Master | 11 | Practice | Leather and footwear |
| 5 | Professional | Master | 16 | Practice | Automobile |
| 6 | Professional | Bachelor | 10 | Practice | Seafood processing |
| 7 | Professional | Bachelor | 12 | Practice | Electronics |
| 8 | Professional | Bachelor | 22 | Practice | Textile and garments |
| 9 | Researcher | PhD | 13 | Academia | Sustainable manufacturing |
| 10 | Researcher | PhD | 16 | Academia | Sustainable development |
| 11 | Researcher | Master | 11 | Academia | Production, supply chain and engineering |
| 12 | Researcher | Master | 11 | Academia | Industrial technology and management |
| 13 | Researcher | Master | 12 | Academia | Sustainable supply chain management |

| | | | | | |
|---|---|---|---|---|---|
| 14 | Researcher | Master | 12 | Academia | Production and operations management |
| 15 | Researcher | Master | 15 | Academia | Digitalization, Industry 4.0 technologies |