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Review

A Systematic Review on Social Sustainability of Artificial Intelligence in Product Design

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Abstract: Emerging technologies such as artificial intelligence help operations management achieve sustainability. However, in sustainable operations management studies, scholars pay less attention to product design, which can be highly affected by artificial intelligence. In addition, sustainability is perceived as maintaining economic development while limiting environmental harm caused by human activity. Therefore, social sustainability is treated as peripheral compared to economic and environmental sustainability. However, social sustainability now has gained more attention because it is the basis on which meaningful economic and environmental sustainability can be valid. Thus, I systematically reviewed present studies on product design considering artificial intelligence to understand what types of social sustainability are achieved when applying artificial intelligence to product design. This study discovered artificial intelligence can improve social sustainability in product design, but social sustainability diversity is necessary. These findings can contribute to the inclusion of different types of social sustainability in product design when using artificial intelligence.

Keywords: sustainable operation; product design; artificial intelligence; social sustainability; systematic review

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1. Introduction

Emerging technologies, as competitive resources, help operations management become more sustainable by meeting the needs of the present and future generations in economic, environmental, and social aspects [1]. The three aspects of sustainability are based on three pillars of sustainability [2]. Sustainable operations management can advance these activities not only in the supply chain of a product but also in new product development, including product design [3]. On top of sustainable operations management, these technologies, such as artificial intelligence, can improve the performance of the activities.

Economic sustainability has been related to operational costs such as production and manufacturing costs [4]. In the economic aspect, association rule mining and decision trees enabled companies to develop a new digital camera [5] and a new smart phone [6] efficiently and effectively. Rough set theory and decision trees helped a manufacturer to design a new notebook visual aesthetic that will decrease consumer complaints and increase user experience [7].

Environmental sustainability has been associated with the reduction of waste, energy, and pollution. In the environmental aspect, fuzzy logic along with analytic network processes advanced the selection of environmentally sustainable product designs [8]. Bayesian decision networks for life-cycle engineering advanced the development of an environmentally friendly oil-drill design [9]. Fuzzy extent analysis and fuzzy technique for order of preference by similarity to ideal solution helped advance green product development [10].

Social sustainability has been connected to the quality of life. In the social aspect, digital fabrication such as 3D printing, CNC milling, and laser cutting for development enabled designers to create products that advanced local employment, empowerment, and ownership. This shows system-centric and radical social sustainability, rather than user-centric and incremental social sustainability [11]. Communication technologies helped industrialization late-comers overcome a mental barrier and promote modernization process by giving them more opportunities for networking [12]. A handheld device by HP, which was a relatively new technology in Uganda, promoted microfinance banking transactions without a one-day journey to a city [13].

However, as the UNEP-SETAC Life Cycle Initiative indicated, the business community has paid less attention to social sustainability because its benefits are intangible and indirect [14]. That is, meeting higher-order needs—e.g., quality of life and safety, and health—were largely not considered in operations management. Studies have tried to measure social sustainability throughout the life of a product. Social sustainability indicators evaluated the needs of employees and customers based on Maslow's hierarchy of individual needs [15]. Zhou et al. (2000) considered maximizing profit for economic sustainability, minimizing resource and energy consumption for environmental sustainability, and maximizing product values by satisfying the market demands for social sustainability [16]. The studies focused on sustainable operations management in the supply chain, not in new product development.

The operations in a supply chain depends on new product development, particularly product design. This is because parts to be made or procured as well as the necessary processes of suppliers, manufacturers, distributors, and retailers are determined in the stage of product design in the supply chain. Thus, it is important to understand socially sustainable operations management in product design. Socially sustainable product design can improve a product's social sustainability by adding customers' design requirements in the product's development and manufacturing process.

It is necessary to understand how new technologies improve product design to become more socially sustainable than economically and environmentally sustainable. Already, many scholars are concentrating on the economic and environmental effects of a powerful new technology, artificial intelligence. Additionally, this is bringing imbalance to sustainability.

Therefore, in this study, I systematically reviewed the highly impactful literatures in product design and artificial intelligence to clarify contributions of artificial intelligence in product design to social sustainability. In particular, this systematic review study was performed based on an efficient systematic review framework [17], and each paper in the literature was identified as involving a combination of three kinds of social sustainability offered by [18]. Through this systematic review, the questions I sought to answer were: (1) What are the contexts of social sustainability in artificial intelligence used in product design? (2) Which scientific communities using artificial intelligence in product design are paying attention to social sustainability? (3) What are the temporal and cross-disciplinary characteristics of social sustainability in artificial intelligence used in product design? (4) How diverse do the types of social sustainability appear in artificial intelligence applied in product design over time and among scientific communities?

By answering the questions, this study discovers the scientific communities paying attention to social sustainability and their characteristics under a certain context of artificial intelligence and product design. This study also opens a new perspective to consider social sustainability types and their diversity in artificial intelligence used in product design. This can reveal our focuses, regarding social sustainability, in artificial intelligence used in product design. This is important where the integration of product and service becomes the center of customer satisfaction under the condition of a digitized and globalized economic environment.

2. Literature Review

Artificial intelligence involves making computers to solve problems in the areas of search, pattern recognition, learning, planning, and induction [19]. It is, in short, a process to study the intelligence to identify useful information processing problems, give a method of how to solve them, and develop algorithms that implement the method [20].

Artificial intelligence is considered to transform human tasks and activities in a wide range of applications [21].

In the case of new product development, artificial intelligence was used in various areas including but not limited to new product development evaluation, product and process design, quality function deployment, conceptual design, and group decision making in concurrent engineering [22]. For example, Santillan-Gutierrez and Wright (1996) applied genetic algorithms to derive promising solutions during the development of a product [23]. Rao et al. (1999) reported that the various areas include but are not limited to problem solving and planning [24], expert systems [25], knowledge-based systems [26], natural language processing [27], robotics [28], computer vision [29], learning [30], genetic algorithms [31], neural networks [32], case-based reasoning [33], rough set theory [34], and intelligent agent [35]. A mixture of various areas of artificial intelligence was also utilized. For example, fuzzy logic, genetic algorithms, and artificial neural networks were applied in design [36].

Artificial intelligence, the most salient and emerging technology currently, is considered to have the power to not only to transform our society but also address societal problems including sustainability [37]. In achieving sustainability everywhere, artificial intelligence, along with other digital technologies, is considered the key transformation element [38]. Artificial intelligence can improve economic, environmental, and social sustainability [39]. However, our attention is still more on economic and environmental sustainability. Artificial intelligence can increase productivity and decrease production costs [40]. It can monitor and reduce emissions [41] and conserve ecosystems [42]. It also can help secure quality and inclusion [43,44]. However, such orientation toward social sustainability seems to have received less attention according to the UNEP-SETAC Life Cycle Initiative [14].

Studies on artificial intelligence for social sustainability seem to be rare. Yet it is the most important type of sustainability to consider [45,46]. Artificial intelligence can secure social sustainability [45]. For instance, artificial intelligence can increase work efficiency and reduce working hours, so that a worker's physical well-being can improve and physical damage caused during working hours can decrease [47]. Artificial intelligence can also perform diverse simple tasks in living spaces, hospitals, and classrooms to serve various small roles in communities [48,49]. Artificial intelligence can automate routine activities in health care [50], education [51], Human Resources [52], call centers [53], and customer services [54]. Artificial intelligence is even able to promote socially charitable and ethical actions [55].

In sustainable operations management, it is necessary to understand the current state of how artificial intelligence used in product design, which many posterior processes are dependent on, contributes to social sustainability. We know little about what scientific community applies what special artificial intelligence in which product design task for a certain aspect of social sustainability. Thus, a literature review on artificial intelligence used in product design from the perspective of social sustainability is required.

When reviewing papers in a certain area, methods can vary according to the size of the papers. If the number of articles is too large, text summarization techniques can extract concepts from the collection of papers. One popular technique is topic modeling. Probabilistic topic modeling is a statistical way to analyze the words of documents to find themes that exist across the words and documents [56]. Among the models that learn patterns of topics in a collection of documents, latent Dirichlet allocation is the simplest and most popular [57]. It discovers topic probability distributions among words embedded in the collection. Recently, given the large amount of textual data, scholars used it for a literature analysis by extracting research trends from the data [58,59]. Lee et al. (2016) used it to derive more abstract concepts from research trends by using the relationships among topics and a community detection algorithm used in network analysis [60]. Song et al. (2016) extended it to regress topic trends on time and venues (i.e., journals) [61]. Such literature analyses were possible due to the rise of algorithms and computational powers as well as available big data.

The size of the literature to be reviewed is not always very large, but can be large enough to prevent researchers from reading all relevant papers for a literature review. In this case, instead of the application of text summarization techniques to literature analyses, scholars used network analysis. Science of science [62] and scientometrics [63,64] and are the research fields that utilize network analysis to map science. Semantic network analysis is an example, and it investigates the associations among the components of the target subject of a literature review, based on the shared meanings of symbols [65]. It is better to use semantic network analysis when the number of the papers is not too large [66]. Lee et al. (2017) used semantic network analysis to understand Parkinson's disease research [67]. Lee and Jung (2019) also employed semantic network analysis to understand social sustainability over time [68].

When the number of the papers is small, researchers can use literature review, and there are three methods for an effective literature review: narrative review, meta-analysis review, and systematic review. Narrative review is an effective literature review that heavily relies on the experience and expertise of the author [69]. It is decomposed into input, processing, and output stages. In the input stage, the quality of literature and the process of gathering papers are the key activities to secure relevant and sufficient data. In the processing stage, the author processes data into information according to Bloom's taxonomy of educational objectives [70]. Finally, in the output stage, the author develops and writes arguments. However, this approach is criticized for its subjectivity. Another effective literature review method is meta-analysis [71,72]. Meta-analysis is a type of observational study of evidence. It is a statistical analysis that integrates the results of different independent studies dealing with a research problem. It is decomposed into problem formulation, data collection and analysis with eligibility criteria and statistical methods, and results reporting with graphical display.

Whereas meta-analysis is known as a quantitative systematic review and results in a quantitative summary, a general systematic review generates a qualitative summary. Both quantitative and qualitative systematic reviews have in common a thoroughly systematic procedure of formulating a specific research question, collecting data with eligibility criteria, and summarizing with a critical appraisal to minimize error and bias. A systematic review has the advantage of summarizing a large collection of studies and explaining differences among studies on the same research question [73]. In the case of understanding the contributions of artificial intelligence used in product design to social sustainability, a statistical combination of the studies is impossible and a qualitative systematic review is appropriate. Thankfully, there is an effective systematic review framework, as outlined by [17].

3. Methodology

To understand the current contribution of artificial intelligence embedded in product design to social sustainability, I refined the efficient systematic literature review framework [17]. This framework involves six steps: scoping, planning, identification and search, screening, eligibility and assessment, and presentation and interpretation (Figure 1). Koutsos et al. (2019) used a case study on agricultural research to confirm the framework's ease of use and efficacy [17].

Through this systematic review process, this study makes answers to (1) What are the contexts of social sustainability in artificial intelligence used in product design? (2) Which scientific communities using artificial intelligence in product design are paying attention to social sustainability? (3) What are the temporal and cross-disciplinary characteristics of social sustainability in artificial intelligence used in product design? (4) How diverse do the types of social sustainability appear in artificial intelligence applied in product design over time and among scientific communities?

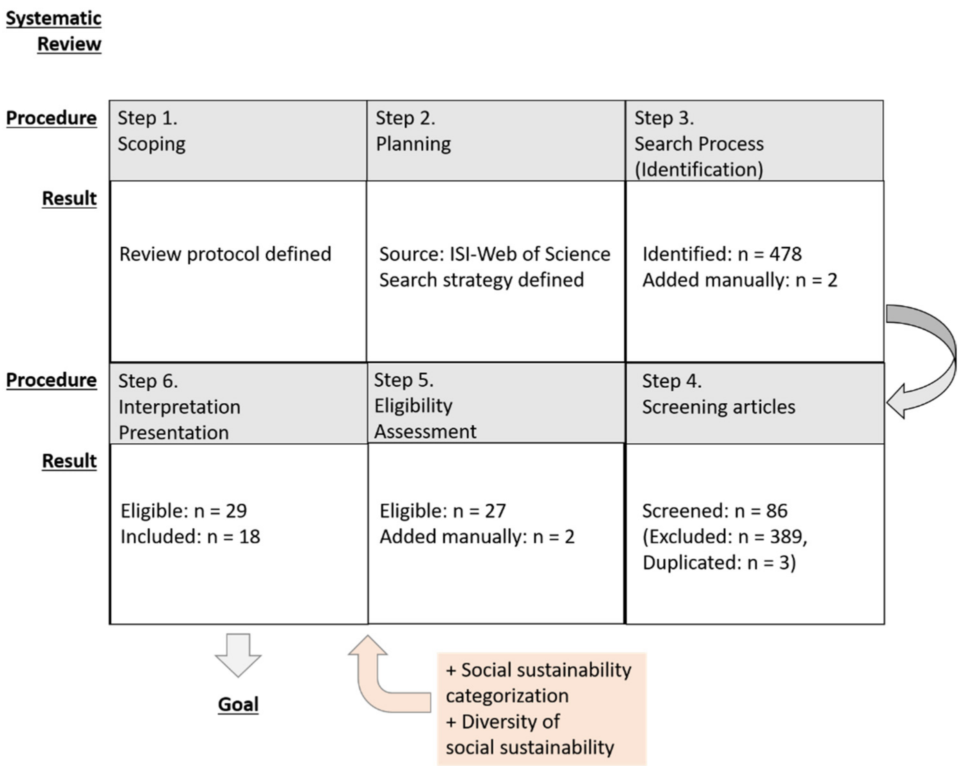

Figure 1. The systematic literature review framework [17] and a refinement focusing on social sustainability (*n* is the number of papers).

The first step is scoping, in which the reviewer defines a protocol for a review. The second step is planning, where the reviewer identifies appropriate databases and develops search strategies. The third step is search process, where the reviewer recognizes papers to include from the databases. In the case study, the authors identified 478 papers and added two papers manually. The fourth step is screening articles, where the reviewer identifies papers to exclude from the papers selected in the previous step. In the case study, the authors excluded 389 papers and three duplicates, leaving 86 papers. The fifth step is eligibility assessment, where the reviewer reads the remaining full-text articles, leaves out papers based on exclusion criteria, and adds papers based on inclusion criteria from other possible sources. In the case study, the authors identified 27 eligible papers to be reviewed and added two more papers from other sources. The last step is interpretation and presentation, where the reviewer synthesizes findings and analyzes the heterogeneity of papers with strong evidence out of eligible papers (11 of 29 papers in the case study). In this step, the reviewer shows the findings graphically and derives their meanings.

In addition, I applied a general inductive approach to the last step to identify themes or categories most relevant to the research objectives identified (Figure 1). A coder uses the typology of social sustainability [18] to identify themes or categories with respect to development, bridge, and maintenance social sustainability. As a result, I can clarify how artificial intelligence used in product design contributes to social sustainability. Additionally, a diversity indicator used in ecology was applied to quantify the heterogeneity among papers (Figure 1).

In detail, the modified efficient systematic literature review framework works as follows. The first step is scoping, which develops focused research questions and study design; identifies a few relevant studies for a pilot review study; and searches for previous systematic reviews on current issues. My focused question was: What are the contributions of artificial intelligence applied in product design to social sustainability, appearing in science? Cai and Choi (2020) recently emphasized the importance of the balance among economic, environmental, and social sustainability in a sustainable supply chain [74].

They showed how economic, environmental, and social sustainability were achieved in sustainable design. Yet consideration of social sustainability is not enough, and the role of technology has not been well examined. There are no previous systematic reviews based on my focused question. Then, I examined the databases and chose the Scopus digital database as the source of search.

The second step is planning. It develops the main search queries using Boolean operators and identifies appropriate digital databases. I developed a query that is an intersection between documents containing "product design" and "artificial intelligence" in the abstract, title, or keywords (author and indexed keywords). That is, in the Scopus database, the query is *(TITLE-ABS-KEY ("product design") AND TITLE-ABS-KEY ("artificial intelligence") AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English"))*. For the selection of articles, the inclusion criteria were (a) the document type is set as "article" and (b) the study was published in peer-reviewed English journals.

Here, the total number of articles containing "product design" and "artificial intelligence" in the abstract, title, or keywords (author and indexed keywords) with the document type article at the initial screening was 392. After refining SCI-indexed journals only, the number of articles was 288. The process of selecting eligible articles based on preferred reporting items for systematic reviews and meta-analyses (PRISMA) [75] is shown in Figure 2.

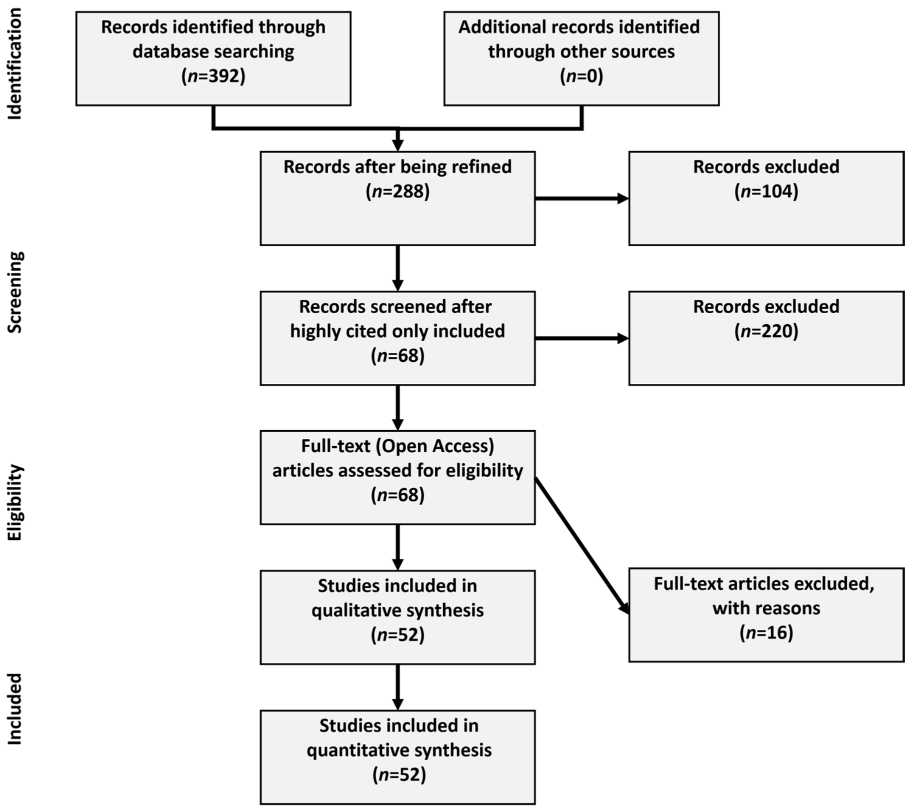

Figure 2. Systematic review flowchart based on systematic reviews and meta-analyses (PRISMA) flowchart.

The third step is identification and search, in which I applied the query developed in the previous step to Scopus DB's search engine. After retrieving relevant articles from Scopus DB, I checked the articles thoroughly to determine if their conditions met eligibility criteria. That is, the conditions were (a) articles containing "product design" and "artificial intelligence" in the title, abstract, and keywords, including author and indexed keywords; (b) the document type is categorized as article in Scopus DB; and (c) the articles were published in peer-reviewed English journals indexed by SCI. Additionally, I checked if the search strategy needed to be changed and if additional searches were necessary.

The fourth step was screening. The bibliographic data of the 288 articles were exported as a CSV file. I again checked duplicates and missing data. Additionally, the highly impactful papers were selected only. I measured the degree of impact using the number of citations. According to pareto principle, which is known as 80/20 rule, I assumed that highly impactful papers were 20% of the total number of papers. Then, the full texts of the selected highly impactful studies were downloaded and examined to determine if they were relevant to product design and artificial intelligence.

The fifth step is eligibility and assessment. I read the full text of the selected articles in depth. Here, I identified if a certain article contained not only keywords such as product design and artificial intelligence but also content relevant to these topics. Finally, I distilled papers on artificial intelligence in product design as shown in Figure 3. I also checked if the article discussed elements that can be categorized as social sustainability. Furthermore, I classify the types of social sustainability associated with the article.

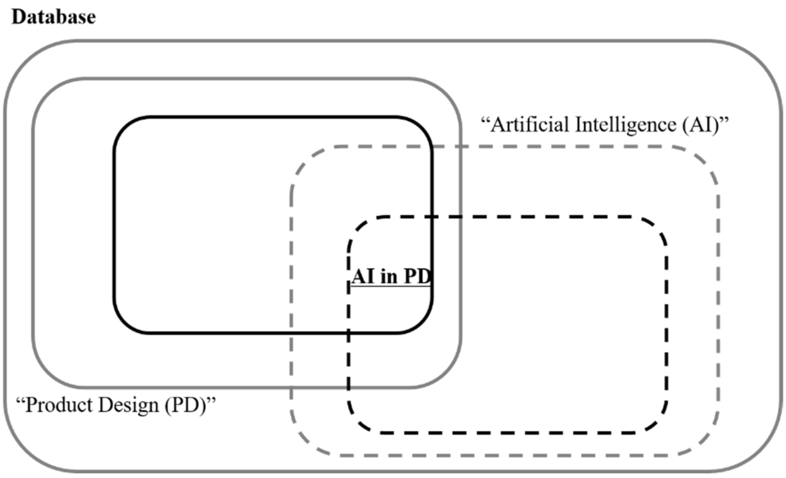

Figure 3. Data selection represented in van diagram.

Sustainability has three pillars: economic, biophysical (i.e., ecological or environmental), and social [2]. Additionally, social sustainability can be decomposed into development, bridge, and maintenance parts [18]. Table 1 summarizes the types of social sustainability. I categorized a study as development social sustainability if it concerned basic needs based on resources and infrastructures. This also can be divided into two parts, tangible and intangible. Studies on economic sustainability can be identified as tangible development social sustainability because economic sustainability encompasses financial costs and benefits, which are directly related to tangible necessities. On the other hand, a study can be identified as having intangible development social sustainability if less tangible needs such as education, employment, equity, and justice are considered. I classified a study as having bridge social sustainability if it included necessary social conditions that sustain ecology or promote attitudes and behaviors that meet the conditions. This can be divided into transformative bridge social sustainability and nontransformative bridge social sustainability. Last, a paper was categorized in maintenance social sustainability if dealt with the ways in which social and cultural preferences and characteristics and the environment are maintained over time to sustain quality of life. Table 2 shows an example of social sustainability type categorization.

To measure the diversity of social sustainability types in artificial intelligence in product design, I use the Shannon diversity index, which is based on Shannon entropy. Let p_i be the proportion of the ith social sustainability type in a document. Then, the diversity of the document, H, is computed using the following equation. For example, if a paper contains tangible development social sustainability, transformative bridge social sustainability, and maintenance social sustainability, then the social sustain inability diversity is –(1/3)log(1/3)

–(1/3)log(1/3) –(1/3)log(1/3). When the value of this index is high, it means highly diverse social sustainability types exist in the paper.

$$H = -\sum_{i=1}^{k} p_i \log(p_i).$$

Table 1. Summary of social sustainability types [18].

<table>
<tr><td colspan="4">Social sustainability: "Social sustainability occurs when the formal and informal processes/systems/structures/relationships actively support the capacity of current and future generations to create healthy and liveable communities." [76]</td></tr>
<tr><td rowspan="2">1.</td><td rowspan="2">Development</td><td rowspan="2">To meet the basic needs, ways to develop infrastructures that secure physical and non-physical requirements</td><td>Tangible: basic physical requirements</td></tr>
<tr><td>Intangible: basic nonphysical requirements</td></tr>
<tr><td rowspan="2">2.</td><td rowspan="2">Bridge</td><td rowspan="2">To support ecological sustainability, ways to promote eco-friendly behavior or stronger environmental ethics</td><td>Transformative: fundamental changes by socially constructed environment</td></tr>
<tr><td>Nontransformative: provision of information for changes</td></tr>
<tr><td>3.</td><td>Maintenance</td><td colspan="2">To sustain quality of life, ways of preferences, characteristics, and environments to be maintained over time.</td></tr>
</table>

Table 2. An example of social sustainability type categorization.

P ID	Development (Tangible)	Development (Intangible)	Bridge (Transformative)	Bridge (Non-Transformative)	Maintenance
1	1	0	0	0	0
. . .					
K	1	1	1	1	1

The sixth step is presentation and interpretation. I started by delineating the context of artificial intelligence used and scientific communities involved. Next, based on the statistics of social sustainability types of all papers, I determined the major social sustainability type, how the social sustainability types change over time, and social sustainability diversity over time and among journals. This enabled me to understand the heterogeneity of the studies included. I identified example papers that contributed different types of social sustainability to read their full texts and distill features of artificial intelligence, product design, and the forms of contributions made to social sustainability. Then, I performed a content analysis on the articles according to their component social sustainability type. For example, to see the characteristics of bridge social sustainability in product design using artificial intelligence, the content analysis only focused on the articles that contain bridge social sustainability.

4. Results

I retrieved bibliographic data that contained "product design" and "artificial intelligence" at the same time in the title, abstract, or keywords from the Scopus database, a major scientific research search engine developed by Elsevier. Here, keywords can be either author or indexed keywords. Author keywords are the representative words that the author inputs, whereas indexed keywords are the representative words that the search engine identifies. Additionally, the retrieved data were from English articles in SCI-indexed journals in the JCR list.

Subsequently, I derived the distribution of the number of citations of the articles, as shown in Figure 4. I confirmed that the majority of the papers had fewer than 26 citation counts. Therefore, I set 26 citations as my threshold for choosing the highly impactful papers, which are shown with an orange box in Figure 4. Figure 5 shows the citation distribution of the selected papers. The most cited paper had more than 600 citations. The number of papers was 68. The number of highly cited papers over time fluctuated (Figure 6). It increased dramatically from 1994 to 2000 and rose until 2007. It then declined in 2007. Since 2007, it has stayed stable, between 10 and 15.

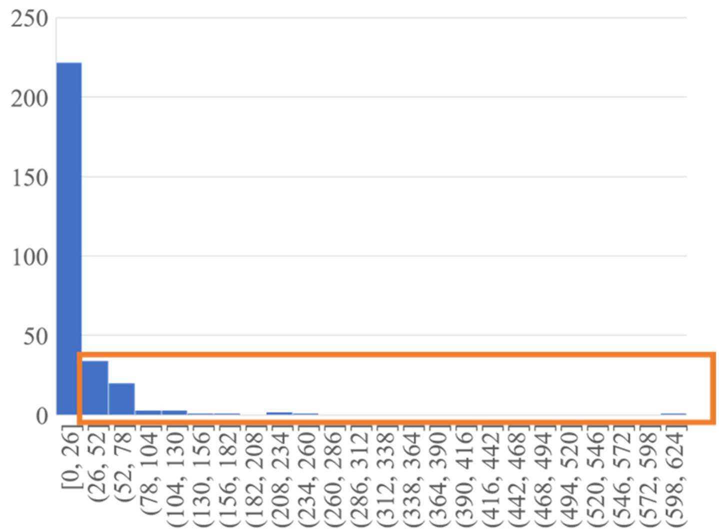

Figure 4. Citation Distribution of the Selected Journal Articles.

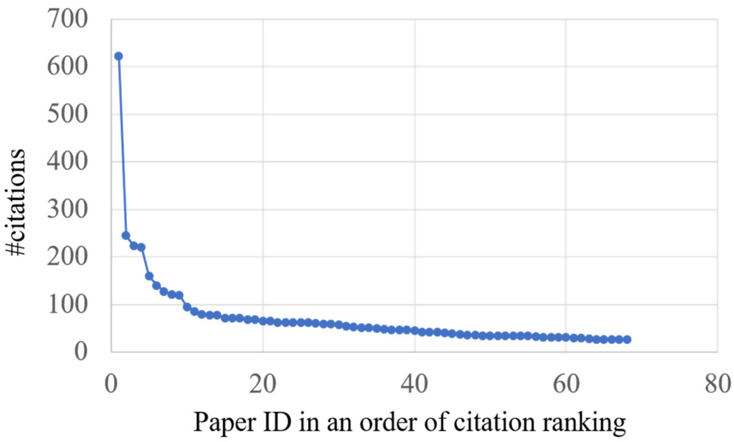

Figure 5. Year Histogram of the Journal Articles of the Final Selection.

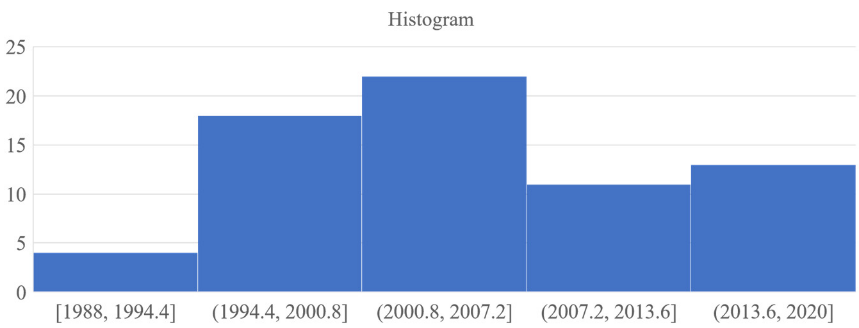

Figure 6. Year Histogram of the Journal Articles of the Final Selection.

Among 68 selected papers, 16 papers were dropped. For every year, the number of publications on artificial intelligence used in product design was stable at two (Figure 7). The 16 papers were excluded because they did not contain either artificial intelligence or product design in the full texts. Ceres et al. (1998) was not about using artificial intelligence in product design but rather the design and implantation of an aided fruit-harvesting robot [77]. Onuh and Yusuf (1999) did not address artificial intelligence but reviewed rapid prototyping technology [78]. Ohashi and Tsujimoto (1999) did not address artificial intelligence but pump research and development review in Japan [79]. Murphy (2001) discussed robot design competition and education [80]. Cavallucci and Weill (2001) focused on how the theory of inventive problem solving can be embedded in design processes [81]. Ahmed and Wallace (2004) developed a method that supports designers and can decrease the frequency of inappropriate questions raised by new designers [82]. Mondada et al. (2004) was about designing swarm intelligent robots, not using swarm intelligence for product design [83]. Far and Elamy (2005) explained functional reasoning theories in engineering design but had no application of functional reasoning to a product design case, so it was hard to find sustainability implications [84]. Whitby (2008) studied designing artificially intelligent robots [85]. Qiu and Benbasat (2014) discussed anthropomorphic information systems design, not product design [86]. Renzi et al. (2014) used artificial intelligence for reconfigurable manufacturing system design, instead of product design [87]. Zhang et al. (2016) was about sustainable supply chain network design optimization rather than product design [88]. Nakandala et al. (2016) used artificial intelligence for the cost-optimization problem of fresh food transportation [89]. Zhang et al. (2017) utilized artificial intelligence to design a supply chain network that maximizes profit [90]. Sanderman et al. (2018) used a random forest model for program design [91]. Liu et al. (2018) used neural networks for a clinical decision support system [92]. Finally, 52 papers were chosen to examine development, bridge, and maintenance social sustainability.

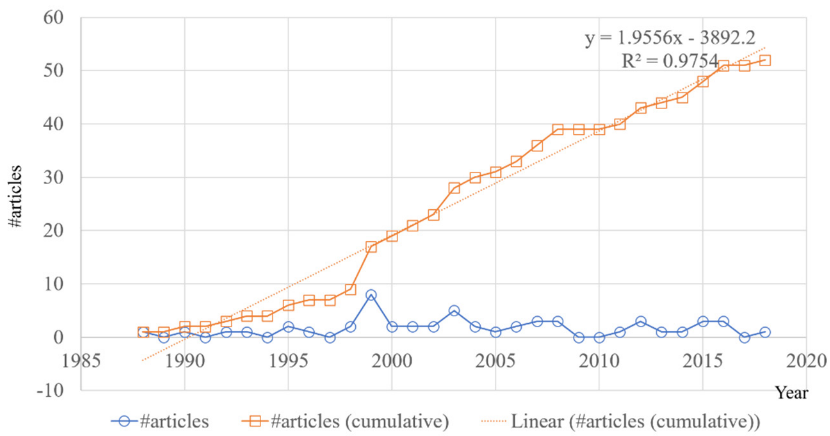

Figure 7. The number of articles on product design and artificial intelligence.

4.1. Contexts

4.1.1. Thematic Context of Social Sustainability in Artificial Intelligence in Product Design

First, by reading the titles of the list in Table 3, I determined that the majority of the papers on artificial intelligence in product design were in the context of assembly manufacturing. Assembly manufacturing considers not only how to design and assemble parts but also how to design and disassemble a product. This allows people to include environment sustainability easily along with economic sustainability. However, recently, additive manufacturing is another context [93,94]. In additive manufacturing, materials and the way of manufacturing a product are different than assembly manufacturing. For instance, we do not have to consider product parts to assemble, but a total product and powder materials to be used.

Table 3. The 52 articles selected with their publication years, source titles, titles, and number of citations.

Paper ID	Year	Source Title	Title	Cited by	Paper ID	Year	Source Title	Title	Cited by
1	2003	International Journal of Machine Tools and Manufacture	Predicting surface roughness in machining: A review [95]	622	33	1999	Research in Engineering Design—Theory, Applications, and Concurrent Engineering	CADOM: A Component Agent-based Design-Oriented Model for collaborative design [96]	51
2	2018	International Journal of Production Research	Smart manufacturing [94]	245	35	1999	Journal of Intelligent Manufacturing	Web-based morphological charts for concept design in collaborative product development [97]	50
5	2003	Research in Engineering Design	Towards an ontology of generic engineering design activities [98]	160	37	2002	Journal of Materials Processing Technology	Case-based reasoning approach to concurrent design of low power transformers [99]	47
6	2002	Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM	Function and behavior representation in conceptual mechanical design [100]	140	39	2004	IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics	Development of Hybrid Genetic Algorithms for Product Line Designs [101]	46
7	2006	Communications of the ACM	Automated analysis of feature models: Challenges ahead [102]	128	40	1999	Research in Engineering Design—Theory, Applications, and Concurrent Engineering	Design support using distributed web-based AI tools [103]	45
8	2004	International Journal of Production Economics	Configuring products to address the customization-responsiveness squeeze: A survey of management issues and opportunities [104]	121	45	2000	International Journal of Production Research	Assembly/disassembly task planning and simulation using expert Petri nets [105]	39
9	2008	Journal of Operations Management	Toward a theory of competencies for the management of product complexity: Six case studies [106]	120	46	1995	Journal of Materials Engineering and Performance	Design for machining using expert system and fuzzy logic approach [107]	38

Table 3. *Cont.*

Paper ID	Year	Source Title	Title	Cited by	Paper ID	Year	Source Title	Title	Cited by
10	2007	Journal of Intelligent Manufacturing	Applying data mining to manufacturing: The nature and implications [108]	95	48	2016	Engineering Applications of Artificial Intelligence	AI-based methodology of integrating affective design, engineering, and marketing for defining design specifications of new products [109]	36
11	1995	Journal of Vibration and Acoustics, Transactions of the ASME	Life-cycle engineering design [110]	86	47	1999	Journal of Intelligent Manufacturing	Artificial intelligence and expert systems applications in new product development—a survey [22]	36
12	2003	Engineering Applications of Artificial Intelligence	Application of Bayesian decision networks to life cycle engineering in Green design and manufacturing [9]	80	49	2001	Computers in Industry	CLOVER: An agent-based approach to systems interoperability in cooperative design systems [111]	35
13	1990	AI Magazine	Assembly sequence planning [112]	78	50	2015	Decision Support Systems	A Decision Support System for market-driven product positioning and design [113]	35
17	2011	Decision Support Systems	A dynamic decision support system to predict the value of customer for new product development [114]	72	53	2006	Advanced Engineering Informatics	Intelligent evaluation approach for electronic product recycling via case-based reasoning [115]	34
18	2012	Advanced Engineering Informatics	Disassembly sequence structure graphs: An optimal approach for multiple-target selective disassembly sequence planning [116]	69	51	1996	Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM	Feature modeling based on design catalogues for principle conceptual design [117]	34

Table 3. *Cont.*

Paper ID	Year	Source Title	Title	Cited by	Paper ID	Year	Source Title	Title	Cited by
19	2001	Engineering Applications of Artificial Intelligence	Knowledge-based approach and system for assembly oriented design, Part I: The approach [118]	68	54	2008	Chemical Engineering Research and Design	Case-based reasoning for chemical engineering design [119]	34
21	1992	International Journal of Production Research	An artificial intelligence-based constraint network system for concurrent engineering [120]	65	52	1998	IEEE Intelligent Systems and Their Applications	A configuration tool to increase product competitiveness [121]	34
22	2003	Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM	Intelligent selective disassembly using the ant colony algorithm [122]	63	55	2015	Waste Management	An investigation of used electronics return flows: A data-driven approach to capture and predict consumers storage and utilization behavior [123]	34
23	2012	Decision Support Systems	A decision support system for integrating manufacturing and product design into the reconfiguration of the supply chain networks [124]	63	56	1999	Annual Review of Fluid Mechanics	Computational fluid dynamics of whole-body aircraft [125]	33
24	2014	International Journal of Advanced Manufacturing Technology	A review on artificial intelligence applications to the optimal design of dedicated and reconfigurable manufacturing systems [87]	63	59	2015	IEEE Robotics and Automation Magazine	Grasping the performance [126]	32
25	2016	Engineering Applications of Artificial Intelligence	A fuzzy TOPSIS and Rough Set based approach for mechanism analysis of product infant failure [127]	62	57	1988	Materials and Design	Planning of expert systems for materials selection [7]	32

Table 3. *Cont.*

Paper ID	Year	Source Title	Title	Cited by	Paper ID	Year	Source Title	Title	Cited by
27	1998	International Journal of Advanced Manufacturing Technology	Integrated intelligent design and assembly planning: A survey [128]	61	61	1993	IEEE Transactions on Engineering Management	Fuzzy Logic Applications: Technological and Strategic Issues [129]	30
29	2008	Expert Systems with Applications	A data mining approach to dynamic multiple responses in Taguchi experimental design [130]	59	62	2007	Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM	A framework for the automatic annotation of car aesthetics [131]	29
28	1999	International Journal of Production Research	Object oriented manufacturing resource modelling for adaptive process planning [132]	59	63	1999	International Journal of Computer Integrated Manufacturing	Integrated knowledge-based approach and system for product design for assembly [133]	28
30	2007	IEEE Transactions on Neural Networks	An approach to estimating product design time based on fuzzy ν-support vector machine [134]	57	64	2003	AI Magazine	Model-Based Computing for Design and Control of Reconfigurable Systems [135]	27
31	2013	International Journal of Production Research	Decarbonising product supply chains: Design and development of an integrated evidence-based decision support system-the supply chain environmental analysis tool (SCEnAT) [136]	54	65	2012	Journal of Manufacturing Systems	Intelligent evaluation of supplier bids using a hybrid technique in distributed supply chains [137]	27
32	2000	Journal of Materials Processing Technology	Designing cable harness assemblies in virtual environments [138]	53	68	2016	Industrial Management and Data Systems	Simulation based method considering design for additive manufacturing and supply chain An empirical study of lamp industry [93]	26
34	1999	Decision Sciences	Linking IT applications with manufacturing strategy: An intelligent decision support system approach [139]	51	67	2005	International Journal of Advanced Manufacturing Technology	A graph and matrix representation scheme for functional design of mechanical products [140]	26

Second, the algorithms of artificial intelligence used in product design include but are not limited to case-based reasoning, genetic algorithms, simulated annealing, ant colony optimization, decision tree, association rule mining, Bayesian network, and fuzzy set theory. Case-based reasoning induces a solution by retrieving the solutions to the cases already stored in a database and reusing or revising the solutions to fit new case needs. Decision tree algorithms generate if–then rules based on information entropy. Association rule mining can also generate rules based on frequent item sets.

Genetic algorithm and its variants are categorized as evolutionary algorithms and imitate a natural selection process including mutation, crossover, and selection to generate combinatoric solutions highly suitable to a certain objective. Simulated annealing is also a kind of evolutionary algorithm that uses a probabilistic technique for deriving globally optimal solutions. Ant colony optimization is a distributed evolutionary algorithm that uses multiple artificial agents search for the global optimal solution. A Bayesian network is a probabilistic graphical model whose nodes are variables and edges are conditional dependencies between nodes. Last, fuzzy logic based on fuzzy set theory helps model human judgement. Basically, artificial intelligence in product design is used to discover the optimal combination of product attributes and parts that maximizes profit and customer's satisfaction while minimizing environmental costs throughout the life of a product.

Third, this artificial intelligence is utilized to not only select attributes and parts of a product but also provide decision supports and cooperative works. A decision support system is an information system that supports design decision-making activities. In this case, the last decision is made by a designer, and the system supplies a list of recommendations that may help the designer narrow the solution search space and determine the optimal solution. In designing a product, sometimes a collaborative product development and concurrent engineering process is necessary. More than one designer work together to make a new product, and creating a team collaboration and cooperation environment is necessary. Additionally, artificial intelligence is used to improve communication and facilitate collaboration.

4.1.2. Scientific Contexts of Social Sustainability in Artificial Intelligence in Product Design

The 52 papers were published in 31 journals (Table 4). The journals that published highly cited papers subject to product design and artificial intelligence include but are not limited to *International Journal of Production Research*, *Artificial Intelligence for Engineering Design, Analysis and Manufacturing (AIEDAM)*, *Engineering Applications of Artificial Intelligence*, *International Journal of Advanced Manufacturing Technology*, *Journal of Intelligent Manufacturing*, *Decision Support Systems*, and *Research in Engineering Design*. Each journal can be characterized by its subject areas and categories by Scopus through Scimago. For instance, *International Journal of Production Research* is in the subject area of business, management, and accounting and its category of strategy and management, in the subject area of decision science and its category of management science and operations research, and in the subject area of engineering and its category of industrial and manufacturing engineering.

According to Scimago's classification system, the 31 journals have 15 subject areas: arts and humanities; business, management, and accounting; decision sciences; engineering; computer science; material science; mathematics; physics and astronomy; chemical engineering; chemistry; psychology; medicine; economics; econometrics and finance; and environmental science. The top three salient subject areas are engineering (19 articles), computer science (18 articles), and business, management, and accounting (seven articles). In engineering, the frequent categories are industrial and manufacturing engineering (12 articles), mechanical engineering (seven articles), and control and systems engineering (five articles). In computer science, the frequent categories are computer science applications (nine articles) and artificial intelligence (eight articles). In business, management, and accounting, the frequent categories are strategy and management (five articles) and management information systems (three articles).

Table 4. The frequency of each journal's published article(s) among the selected 52 articles.

Journal Name	#Articles
International Journal of Production Research	5
Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM	4
Engineering Applications of Artificial Intelligence	4
International Journal of Advanced Manufacturing Technology	3
Journal of Intelligent Manufacturing	3
Decision Support Systems	3
Research in Engineering Design—Theory, Applications, and Concurrent Engineering	3
Advanced Engineering Informatics	2
AI Magazine	2
Journal of Materials Processing Technology	2
Annual Review of Fluid Mechanics	1
Chemical Engineering Research and Design	1
Communications of the ACM	1
Computers in Industry	1
Decision Sciences	1
Expert Systems with Applications	1
IEEE Intelligent Systems and Their Applications	1
IEEE Robotics and Automation Magazine	1
IEEE Transactions on Engineering Management	1
IEEE Transactions on Neural Networks	1
IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics	1
Industrial Management and Data Systems	1
International Journal of Computer Integrated Manufacturing	1
International Journal of Machine Tools and Manufacture	1
International Journal of Production Economics	1
Journal of Manufacturing Systems	1
Journal of Materials Engineering and Performance	1
Journal of Operations Management	1
Journal of Vibration and Acoustics, Transactions of the ASME	1
Materials and Design	1
Waste Management	1
Total	52

4.2. Social Sustainablity Categorization

4.2.1. Skewness to the Development Social Sustainability

I confirmed that development social sustainability, especially the tangible form, is the main sustainability type (Table 5). All the papers collected and identified as addressing artificial intelligence applied in product design considered the elements of tangible development social sustainability. However, only 11 of the 52 papers (i.e., 21.15%) considered bridge social sustainability. Eight of the 52 papers (i.e., 15.38%) considered maintenance social sustainability. It seems that scholars care more about developmental social sustainability than bridge social sustainability, and bridge social sustainability more than maintenance social sustainability. That is, in artificial intelligence used in product design, meeting physical needs is considered first. The concerns about behavioral changes to achieve environmental goals comes next. Keeping up values during economic and social changes is the last thing to consider.

In addition, tangible development social sustainability was found far more frequently than intangible development social sustainability. Whereas all 52 studies were related to tangible development social sustainability, just one study was related to intangible development social sustainability. Tangible basic needs were counted more than less tangible needs such as education, employment, equity, and justice. Transformative bridge social sustainability was discovered more frequently than nontransformative bridge social sustainability. Eleven studies on bridge social sustainability were all transformative. Among them, only one was relevant to nontransformative bridge social sustainability. Namely, in product design, artificial intelligence is changing fundamental ways to make an eco-friendlier product. Last, maintenance social sustainability was the least common form of social sustainability found. As Vallance et al. (2009) indicated, preserving sociocultural values in the environment of social and economic changes seem to be overlooked in artificial intelligence used in product design [18].

4.2.2. The Small Rise of Social Sustainability

Scholars have been considering social sustainability effect of artificial intelligence in product design more, although the extent of their consideration seems to be insufficient (Table 6). Over the years, development social sustainability has been included constantly. Development social sustainability was considered more after 1995, indicated by its upward trend. However, the trend is slightly incremental. Additionally, the majority of development social sustainability was tangible rather than intangible. Furthermore, bridge social sustainability was considered from time to time and transformative was included only rarely. Like bridge social sustainability, maintenance social sustainability has been considered occasionally. The year 2013 seems to be when diverse social sustainability was addressed.

Across journals, development social sustainability is also the main type. Ten of the 31 journals that published these 52 papers only contained the other social sustainability types. *International Journal of Production Research* is a good example that contained all types of social sustainability. *Waste Management* contained tangible development social sustainability, transformative bridge social sustainability, and maintenance social sustainability. The other eight journals included either transformative bridge social sustainability or maintenance with tangible development social sustainability. The remaining 21 journals only considered tangible development social sustainability.

In sum, either explicitly or implicitly, social sustainability was considered in the literature of product design using artificial intelligence constantly but to a small extent. However, in terms of social sustainability types, development social sustainability has been the main incremental attention over time and among journals. Subsequently, various types of social sustainability should be dealt with more in studies of artificial intelligence used in product design. To examine the necessity of social sustainability heterogeneity, I looked at the diversity of social sustainability among the 52 papers with respect to time and venues of publication.

Table 5. Social sustainability type categorization results.

Paper ID	Development-Tangible	Development-Intangible	Bridge-Transformative	Bridge-NonTransformative	Maintenance	Paper ID	Development-Tangible	Development-Intangible	Bridge-Transformative	Bridge-NonTransformative	Maintenance
1	1	0	0	0	0	33	1	0	0	0	0
2	1	0	1	0	1	35	1	0	0	0	0
5	1	0	0	0	0	37	1	0	1	0	0
6	1	0	0	0	0	39	1	0	0	0	1
7	1	0	0	0	0	40	1	0	0	0	0
8	1	0	0	0	0	45	1	0	0	0	0
9	1	0	0	0	0	46	1	0	0	0	0
10	1	0	0	0	0	48	1	0	0	0	0
11	1	0	1	0	0	47	1	0	0	0	1
12	1	0	1	0	0	49	1	0	0	0	0
13	1	0	0	0	0	50	1	0	0	0	1
17	1	0	0	0	0	53	1	0	1	0	0
18	1	0	1	0	0	51	1	0	0	0	0
19	1	0	0	0	0	54	1	0	0	0	0
21	1	0	1	0	0	52	1	0	0	0	1
22	1	0	1	0	0	55	1	0	1	0	1
23	1	0	0	0	0	56	1	0	0	0	0
24	1	0	0	0	0	59	1	0	0	0	0
25	1	0	0	0	0	57	1	0	0	0	0
27	1	0	0	0	0	61	1	0	0	0	0
29	1	0	0	0	0	62	1	0	0	0	0
28	1	0	0	0	0	63	1	0	0	0	0
30	1	0	0	0	0	64	1	0	0	0	0
31	1	1	1	1	1	65	1	0	0	0	0
32	1	0	0	0	1	68	1	0	1	0	0
34	1	0	0	0	0	67	1	0	0	0	0
						Total	52	1	11	1	8

Table 6. The types of social sustainability over both time and by venue of publication.

Journal Name.	1988	1990	1992	1993	1995	1996	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2011	2012	2013	2014	2015	2016	2018	Total
International Journal of Production Research			1,0,1,0,0					1,0,0,0,0	1,0,0,0,0											1,1,1,1,1				1,0,1,0,1	5,1,3,1,1
Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM						1,0,0,0,0					1,0,0,0,0	1,0,1,0,0				1,0,0,0,0									4,0,1,0,0
Engineering Applications of Artificial Intelligence										1,0,0,0,0		1,0,1,0,0											2,0,0,0,0		4,0,1,0,0
International Journal of Advanced Manufacturing Technology							1,0,0,0,0							1,0,0,0,0							1,0,0,0,0				3,0,0,0,0
Journal of Intelligent Manufacturing								2,0,0,0,1								1,0,0,0,0									3,0,0,0,1
Decision Support Systems																		1,0,0,0,0	1,0,0,0,0			1,0,0,0,1			3,0,0,0,1
Advanced Engineering Informatics															1,0,1,0,0				1,0,1,0,0						2,0,2,0,0
AI Magazine		1,0,0,0,0										1,0,0,0,0													2,0,0,0,0
Journal of Materials Processing Technology									1,0,0,0,1		1,0,1,0,0														2,0,1,0,1
Research in Engineering Design—Theory, Applications, and Concurrent Engineering								2,0,0,0,0				1,0,0,0,0													3,0,0,0,0
Annual Review of Fluid Mechanics								1,0,0,0,0																	1,0,0,0,0
Chemical Engineering Research and Design																	1,0,0,0,0								1,0,0,0,0
Communications of the ACM															1,0,0,0,0										1,0,0,0,0
Computers in Industry										1,0,0,0,0															1,0,0,0,0
Decision Sciences								1,0,0,0,0																	1,0,0,0,0
Expert Systems with Applications																	1,0,0,0,0								1,0,0,0,0
IEEE Intelligent Systems and Their Applications							1,0,0,0,1																		1,0,0,0,1
IEEE Robotics and Automation Magazine																						1,0,0,0,0			1,0,0,0,0

Table 6. *Cont.*

Journal Name.	1988	1990	1992	1993	1995	1996	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2011	2012	2013	2014	2015	2016	2018	Total
IEEE Transactions on Engineering Management				1,0,0,0,0																					1,0,0,0,0
IEEE Transactions on Neural Networks																1,0,0,0,0									1,0,0,0,0
IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics													1,0,0,0,1												1,0,0,0,1
Industrial Management and Data Systems																							1,0,0,0,0		1,0,0,0,0
International Journal of Computer Integrated Manufacturing								1,0,0,0,0																	1,0,0,0,0
International Journal of Machine Tools and Manufacture												1,0,0,0,0													1,0,0,0,0
International Journal of Production Economics													1,0,0,0,0												1,0,0,0,0
Journal of Manufacturing Systems																			1,0,0,0,0						1,0,0,0,0
Journal of Materials Engineering and Performance					1,0,0,0,0																				1,0,0,0,0
Journal of Operations Management																	1,0,0,0,0								1,0,0,0,0
Journal of Vibration and Acoustics, Transactions of the ASME					1,0,1,0,0																				1,0,0,0,0
Materials and Design	1,0,0,0,0																								1,0,0,0,0
Waste Management																						1,0,1,0,1			1,0,1,0,1
Total	1,0,0,0,0	1,0,0,0,0	1,0,1,0,0	1,0,0,0,0	2,0,1,0,0	1,0,0,0,0	2,0,0,0,1	8,0,0,0,1	2,0,0,0,1	2,0,0,0,0	2,0,1,0,0	5,0,2,0,0	2,0,0,0,1	1,0,0,0,0	2,0,1,0,0	3,0,0,0,0	3,0,0,0,0	1,0,0,0,0	3,0,1,0,0	1,1,1,1,1	1,0,0,0,0	3,0,1,0,2	3,0,0,0,0	1,0,1,0,1	52,1,11,1,8

4.2.3. Necessary Social Sustainability Diversity

When applying Shannon diversity to the numbers in Table 6, the overall Shannon diversity index of the five types of social sustainability was 0.887. The Shannon diversity index is high when the heterogeneous types are distributed evenly and low otherwise. As 0.887 is not that high of a value, this shows the low and imbalanced diversity of social sustainability in the literature on product design using artificial intelligence. I also considered the diversity of social sustainability types over time and among journals.

Over the years, the average and standard deviation of the Shannon diversity index values of all journals were 0.406 and 0.446, respectively. The diversity of social sustainability types has been low. The maximum was 1.609 in 2013. The trend of social sustainability type diversity is going up slightly (Figure 8). My guess is that the period between 2007 and 2011 seems to a change point. There seems to be a discontinuity before and after this period. It may be that awareness of social sustainability and the balance among different types of sustainability grew prominently after the 2008 financial crisis.

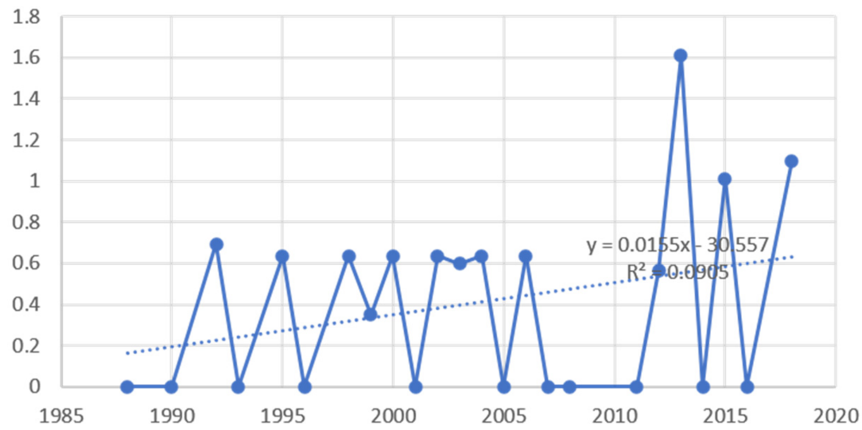

Figure 8. The diversity of social sustainability types over time.

Among journals, the average and standard deviation of the Shannon diversity index values of all journals were 0.249 and 0.401, respectively. The diversity of social sustainability types has been low across the journals. The maximum was 1.367 in *International Journal of Production Research*, which is one of the leading journals in production research (Figure 9). Only three journals that published the included papers were found to be saliently diverse and balanced in terms of social sustainability types.

4.3. Content Analysis

4.3.1. Big Data and Artificial Intelligence

Big data and artificial intelligence can make product design not only smarter but also more sustainable. According to my results, three publications contributed to development, bridge, and maintenance social sustainability [93,94,136]. Kusiak (2018) emphasized sustainability as one of six pillars of smart manufacturing [94]. It is not what we make but how we make it that can contribute to sustainability. Additionally, artificial intelligence mostly involves the process of product design. In case of a smart vehicle, the sustainable design of e-vehicles results in autonomous, personal, shared, and sustainable transportation that may improve economic, environmental, and social sustainability.

Additionally, the environment of additive manufacturing gives more flexibility to product design, using artificial intelligence based on big data. In the six pillars of smart factory that Kusiak (2018) suggested, manufacturing technology and processes change in accordance with the emergence of new materials, components, and products [94]. In the case of biomanufacturing, using artificial intelligence to generate possible bioprinting scenarios and select parameters in bioprinted product design enables high-throughput biofabrication [141].

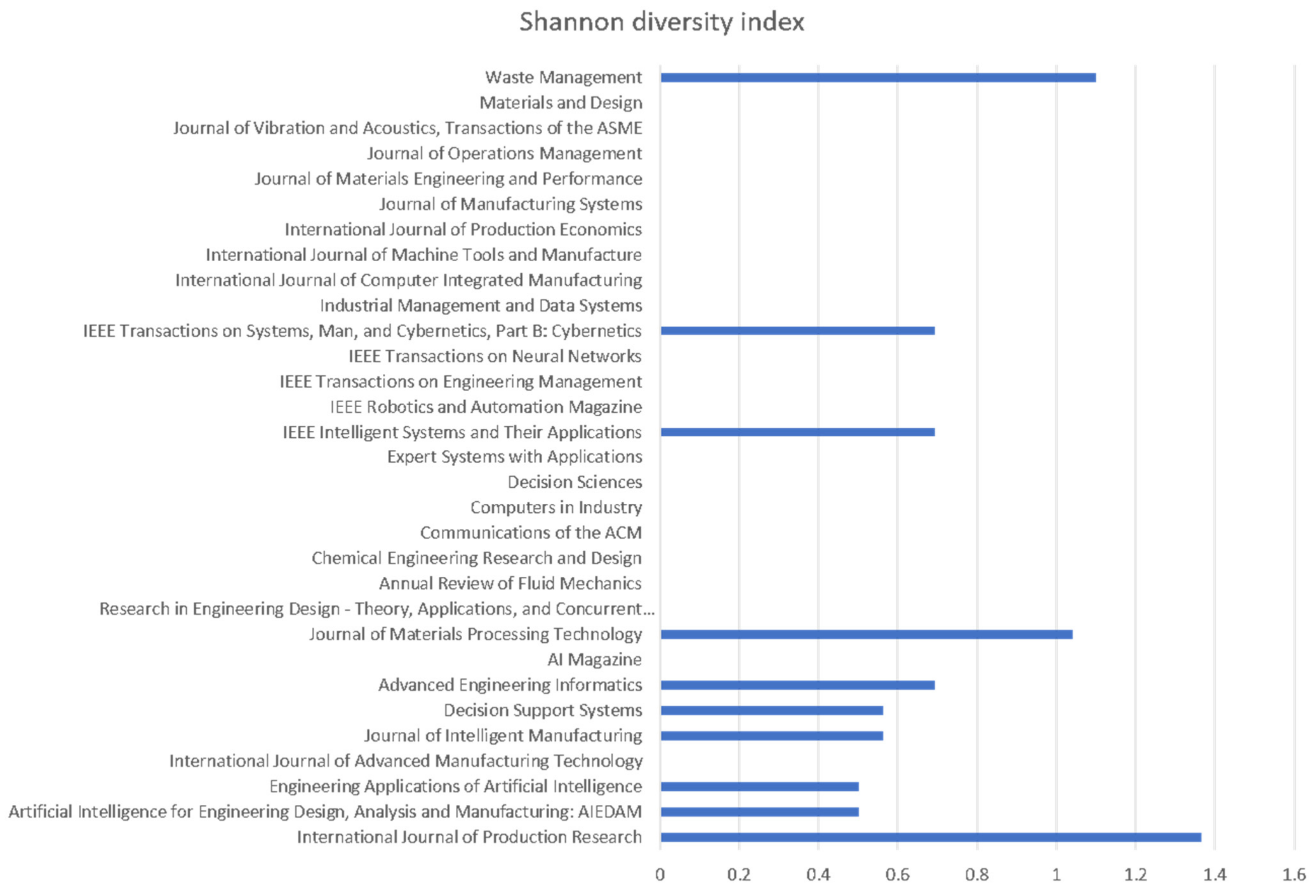

Figure 9. The diversity of social sustainability types among journals.

4.3.2. Bridge Social Sustainability by Considering Product Life Cycle

Bridge social sustainability was mainly achieved by considering product life cycle. Young et al., (1992) used artificial intelligence constraint networks to support designers in concurrent engineering, which help designers handle life-cycle information requirements in printed wiring board manufacturing [120]. Ishii (1995) considered product life-cycle values such as functional performance, manufacturability, serviceability, and environmental impact in life-cycle engineering design [110]. One scholar applied semantic networks [142] to manufacturing for automated reasoning about product design. He specifically stated that “Life-cycle engineering seeks to maximize a product’s contribution to the society while minimizing its cost to the manufacturer, the user and the environment.” Kwong and Tam (2002) utilized case-based reasoning in the concurrent product and process design of low-power transformers to aid designers in improving the lead time and quality of product and process design [99]. Zhu and Deshmukh (2003) used Bayesian decision networks, which are helpful to represent and reason about decision problems under uncertainty, in green design and manufacturing [9]. Wang et al. (2003) used ant colony algorithms to intelligently generate disassembly sequences for the chosen components, which also minimized the reorientation of assemblies and removal of components [122]. Shih et al. (2006) used case-based reasoning to select a recycling strategy and evaluate the performance of disassembly operations [115]. Smith et al. (2012) introduced a disassembly sequence structure graph model for multiple-target selective disassembly sequence planning to improve solution quality, reduce model complexity, and minimize search time [116].

4.3.3. Maintenance Social Sustainability by Supporting Meeting Demand Preference

Maintenance social sustainability mostly was achieved by supporting designers to meet demand preferences when designing a product. Yu and Skovgaard (1998) introduced

SalesPLUS, a product-configuration tool based on artificial intelligence, enabling designers to effectively make configurations that meet customer demands and reduce costs [121]. Ng et al. (2000) developed a cable harness design and planning using artificial intelligence and tested usability [138]. Balakrishnan et al. (2004) used hybrid genetic algorithms for product line designs [101]. According to their implications, it is necessary not only to maximize market share but also to minimize undesirable organizational conflicts and inequity. Lei and Moon (2015) applied principal component analysis, k-means clustering, and AdaBoost classification to determine new product design and positioning in market segments and support designers by providing recommended scenarios of product development [113].

5. Discussion

5.1. More Than Economic and Environmental Sustainability

The slowly growing number of the articles including social sustainability consideration among the highly cited articles on product design using artificial intelligence implies that social sustainability is not considered as often as economic and environmental sustainability, as many scholars have indicated. Even the articles considering social sustainability were mostly rooted in economic and environmental sustainability. In particular, the articles on product design included but were not limited to using artificial intelligence tend to regard economic sustainability in default and increasingly study environmental sustainability. It seems this is because the definition of social sustainability is unclear. Even if there is a certain framework or definition for social sustainability, it is not well known and recognized by people. A similar phenomenon is shown with social sustainability as well. Social sustainability related to infrastructure supporting tangible and intangible needs, i.e., development social sustainability, has been more often included than social sustainability regarding transformative and less transformative eco-friendly actions, i.e., bridge social sustainability. Additionally, bridge social sustainability is more incorporated than social sustainability regarding maintaining values when changes occur, i.e., maintenance social sustainability. In sum, even in product design using artificial intelligence, materials and tangible environment come first rather than intangible values. This may lead our society to become more materialistically prosperous than ever but mentally devastated.

5.2. Diversity and Harmony

When promoting social sustainability, which is less tangible than economic and environmental sustainability, we need to be aware of the existence of an insufficiently balanced social sustainability in social sustainability types. Otherwise, it may lead to poor social sustainability in designing a new product using artificial intelligence. Diversity in social sustainability can be achieved by showing the state of the poor social sustainability in our research—product design using artificial intelligence in this case—and developing appropriate indicators for insufficient social sustainability types such as maintenance social sustainability in every step where artificial intelligence is used in product design.

Not only balance among development, environmental, and maintenance social sustainability but also harmony among them is required. We do not know the golden ratio of how to combine different social sustainability types. Additionally, equal attention is not needed to the social sustainability types, but equitable attention is required. Development social sustainability is well understood, but maintenance social sustainability is not. One way to improve this is to encourage researchers in scientific communities who write papers in the journals listed in this study to consider maintenance and bridge social sustainability.

We can promote diverse social sustainability in harmony by first identifying the stages of product design where artificial intelligence is utilized and a certain type of social sustainability is achieved. Once we clarify the relationship among a product design stage, artificial intelligence algorithm, and social sustainability type, we can concentrate on a specific product design and artificial intelligence algorithm to contribute to the growth of a target social sustainability type.

6. Conclusions

Artificial intelligence can help operations management be more economically, environmentally, and socially sustainable. However, as many scholars indicated, socially sustainable operations management has received less attention than economically and environmentally sustainable operations management. At the same time, social sustainability is now getting more attention because it is the basis of economic and environmental sustainability. In this circumstance, I consider that product design in sustainable operations management should be highlighted more because it determines the following operations in the supply chain of a product. In fact, product design has evolved with the help of computers. Thus, artificial intelligence is expected to improve the performance of product design economically, environmentally, and socially.

Unlike economic sustainability and environmental sustainability, social sustainability has not been foregrounded in considering the effect of artificial intelligence in product design. Therefore, in this study, I systematically reviewed the literature on product design using artificial intelligence to appraise the contributions of artificial intelligence in product design to social sustainability. This review was done by following PRISMA [75] and an effective systematic review framework [17] tuned to my settings. Social sustainability can be categorized into development, bridge, and maintenance social sustainability, based on [18], so a coder can check if a certain study contains the elements of the three different types of social sustainability.

As a result, I first found the contexts of social sustainability generated by artificial intelligence in product design. Assembly manufactured products, rather than additive manufactured products, are more often considered. Algorithms in artificial intelligence are various, but many are based on the previous cases and generate combinatoric solutions, including product attributes and rules. They are applied not only in product design itself but also in supporting decisions in product design. Next, I discovered the major scientific communities that contribute to product design using artificial intelligence. According to Scimago's classification system, the top three communities were engineering, computer science, and business.

The second finding is based on the statistics derived from the classification of social sustainability types of each article. Not surprisingly, the social sustainability associated with physical and nonphysical infrastructure to support basic needs, which is development social sustainability, was dominant. This leads to an imbalance among kinds of social sustainability over time and by venue of publication. Social sustainability diversity seems to be necessary, but one good sign is that the consideration of social sustainability has increased, although its extent is small.

Based on knowledge of the contexts and contributions of the papers to different types of social sustainability, I confirmed that big data and artificial intelligence contribute to making product design not only smart but also sustainable. I also verified that bridge social sustainability is often achieved when considering the life cycle of a product. Achieving maintenance social sustainability is somewhat blurry, but it mostly involves meeting demand preference. As our economy is more digitized and globalized, servitization becomes important and artificial intelligence can help product design integrate product and service to improve social sustainability.

This study had limitations. I used one major database in this study, but there are several other resources for information retrieval on a certain topic. Additionally, I only considered papers that are highly cited by scholars. In addition, the classification and annotation of the types of social sustainability were done by a coder manually. This can be performed by machine learning algorithms for classification. Moreover, the types of social sustainability are not mutually exclusive.

The future directions are five folds. First, databases such as Web of Science can be considered in addition to Scopus. Second, digital product design can be included in addition to physical product design. For example, AI chatbot design in COVID-19 pandemic can be incorporated to cover health in social sustainability [143]. Third, all the papers can be included instead of highly cited papers. Fourth, multiple coders or automatic coders can be used in classification of social sustainability types. Fifth, the relationships among social sustainability types can be studied more.

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