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Infoecology of the deep learning and smart manufacturing: thematic and concept interactions

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Abstract

Purpose – This infecological study mainly aimed to know the thematic and conceptual relationship in published papers in deep learning (DL) and smart manufacturing (SM).

Design/methodology/approach – The research methodology has specific research objectives based on the type and method of research, data analysis tools. In general, description methods are applied by Web of Science (WoS) analysis tools and Voyant tools as a web-based reading and analysis environment for digital texts. The Yewno tool is applied to draw a knowledge map to show the concept's interaction between DL and SM.

Findings – The knowledge map of DL and SM concepts shows that there are currently few concepts interacting with each other, while the rapid growth of technology and the needs of today's society have revealed the need to use more and more DL in SM. The results of this study can provide a coherent and well-mapped road map to the main policymakers of the field of research in DL and SM, through the study of coexistence and interactions of the thematic categories with other thematic areas. In this way, they can design more effective guidelines and strategies to solve the problems of researchers in conducting their studies and direct. The analysis results demonstrated that the information ecosystem of DL and SM studies dynamically developed over time. The continuous conduction flow of scientific studies in this field brought continuous changes into the infoecology of subjects and concepts in this area.

Originality/value – The paper investigated the thematic interaction of the scientific productions in DL and SM and discussed possible implications. We used of the variety tools and techniques to draw our own perspective. Also, we drew arguments from other research work to back up our findings.

Keywords Infoecology, Information ecology, Thematic interaction, Concept interaction, Smart manufacturing (SM), Deep learning (DL), Web of Science (WoS), Artificial intelligence (AI)

Paper type Research paper

1. Introduction/background

Deep learning (DL) is a sub-scan of machine learning that uses multiple layers of linear transformations to process sensory signals, such as sound and image. The machine divides each complex concept into simpler concepts. By continuing this process, it comes to basic concepts that are able to make decisions for them. Thus, there is no need for complete human monitoring to specify the machine's information at any moment. The subject matter of DL is important in providing information. Providing information to the machine should be such that the machine receives the critical information it can decide upon by citing it in the shortest possible time. Here, smart manufacturing (SM) is an integration between artificial intelligent (AI) and manufacturing techniques. AI techniques, such as machine learning, neural network, evolutionary algorithms and fuzzy techniques, are adopted to automate the recognition and

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decision-making in manufacturing. At the other hand, agile innovation and manufacturing combined with radically increased productivity become engines for competitiveness and reinvestment, not simply for a decreased cost. A focus on agility, productivity, energy and environmental sustainability produces opportunities that are far beyond reducing market volatility. Agility directly impacts innovation, time-to-market and faster, broader exploration of the trade space. These changes, the forces driving them and new network-based information technologies offering unprecedented insights and analysis motivate the advent of SM and new information technology infrastructure for manufacturing (Davis *et al.*, 2015). Infoecology considers information space as an infoecosystem. Infoecology studies "the relationship between individuals, activities, technologies and information environment." In an infoecosystem, such as an ecosystem, there are two main factors, including the information environment and information elements. In infoecosystem, the information environment calls "Infotope," and information elements calls "Infocenose" (Asemi and Ko, 2021). Here, we needed to know the relationship between the scientific papers in the field of DL and SM. On the other hand, there were no infoecologic's approaches in the field of DL and SM to show the theoretical relationship between scientific papers in this field. In the present study, infoecology was mainly limited to the thematic interaction of scientific papers on DL and SM in Web of Science (WoS). The purpose was not to examine all user, technology and other interactive features in the information environment. This research has focused on the subject matter and concept matter interactions with an infoecological approach. The following specific objectives are considered in the study:

(1) To analyze the main thematic categories associated with SM in the scientific papers (WoS) with emphasis on thematic interaction.

(2) To analyze the main thematic categories associated with DL in the scientific papers (WoS) with emphasis on thematic interaction.

(3) To analyze the main thematic categories associated with DL and SM in the scientific papers (WoS) with emphasis on thematic interaction.

(4) To present a general knowledge map on the concept interaction in the field of DL and SM.

2. Literature review

In information science and scientometrics, numerous research studies are conducted in the analysis of thematic structures of published articles. Today, the semantic analysis of texts do with new generation web tools. Scientific mapping is done with various methods, techniques, and tools. These studies are usually done with the intention of providing a clearer way for strategic planning for future scientific research. Various techniques, methods and tools are used by researchers for the thematic and conceptual analysis of scientific publications. These include methods and tools for classifying topics, clustering topics, visualizing data and information to draw knowledge maps and thematic or concept modeling. Blessinger and Frasier (2007) categorized articles in librarianship and information science. Chen *et al.* (2008) used clustering, thematic structure and concepts extracted using concept maps and network visualization. Lee and Su (2011) showed the state of scientific research in conductive polymer nanocomposites using the scientific mapping method. Leiva (2012) examined user behavior using word analysis and bibliometric methods. Wang *et al.* (2013) conducted an interdisciplinary study in nano using keyword extraction of published sources. Thematic and conceptual analysis is performed on two categories of structured data and unstructured data. Olaoye *et al.* (2019) performed thematic analysis by qualitative analysis in the social responsibility area. Arboleda *et al.* (2020) collected data from potential end users with

physical disabilities. Other necessary data also collected from social workers and supervisors using the participatory design technique. They analyzed the data using thematic analysis to identify key issues. Kiani *et al.* (2020) in their study represented an infoecology of bioinformatics, with an emphasis on the topic of relationships between studies to provide a scientific framework for infoecological investigations in this field. Also, there are other research studies on various topics in the field of information ecology in recent years (Ma, 2021; Wang, 2021; Jin and Yu, 2021). Lochmiller (2021) performed thematic analysis using structured qualitative data collected from focus groups. Lopez-Robles *et al.* (2021) by combining two methods of bibliometrics and thematic analysis using SciMAT performed the thematic analysis in AI. They identified the main thematic areas in this area. The amount of this tendency depends on the selected indicators. The results show that the techniques used in the nanoscale research areas are changed over time. Scientific conclusions and citation analysis also confirm that nanotechnology has developed into a relative maturity stage and has become a standardized and standardized technology. Table 1 shows brief bibliography information of the published papers on DL and SM during recent years.

This study does not examine all features, such as user, technology and other interactive features, in the information environment. This research mainly provided the thematic interaction and concept interaction of the indexed scientific papers in the WoS based on the infoecologic's approach.

3. Methodology

The research methodology is explained into each of the research objectives based on the type and method of research, data analysis tools. This research is of quantitative descriptive type. Descriptive statistics were used to analyze the data. Three web-based data analysis tools were used to answer research questions. In general, description methods are applied by WoS analysis tools and Voyant tools as a web-based reading and analysis environment for digital texts. The Yewno tool is applied to draw a knowledge map to show the concept interaction between DL and SM. Tables 2 and 3 show the methodological overview of the present study in terms of research objective, statistical population, data collection tools, data preparation tools and data analysis tools.

In this study, the Voyant tool was used to analyze the text of the categories extracted in the field of DL and SM from the WoS. Voyant is a web-based reading and scientific interpretation environment designed to facilitate reading and interpreting techniques for researchers. This tool can be used to read edited texts. To develop the tools, researchers can also use the code definition feature in Voyant. Several steps of data cleaning were carried out to enter the Voyant. In each step, by testing the cleared data in Voyant, the redundant data were exposed, the cleaning operation was performed again and finally, the data were normalized. Finally, after the last data cleaning, it was ready for analysis in Voyant. In data cleaning, some operations were applied, such as removing extra spaces between words, removing extra spaces between paragraphs, deleting punctuation, deleting stop words, deleting prepositions, deleting conjunctions, deleting obscure or meaningless words, unification of different forms of subject words, replacement of synonyms, unification of plural and singular forms. Finally, the text format containing a single document in Voyant was analyzed using JSON format. The findings were illustrated in the following ways to draw infoecology:

(1) Thematic categories cloud;

(2) Repetitive thematic trend relative to each other using Pearson correlation coefficient between pairs of repetitive thematic categories in WoS and

(3) Loom's perspective on how to distribute high-frequency thematic categories.

No.	Title	Date	Publisher
1	Ensuring the robustness and reliability of data-driven knowledge discovery models in production and manufacturing (Tripathi *et al.*, 2021)	Jun 2021	Frontiers Media SA
2	Predictive maintenance and intelligent sensors in smart factory: Review (Pech *et al.*, 2021)	Feb 2021	MDPI AG
3	Neuroscience Inspired algorithms for the predictive maintenance of manufacturing systems (Malawade *et al.*, 2021)	Jan 2021	eScholarship, University of California
4	Construction of digital twin ecosystem for coal-fired generating units (Yan, 2021)	Jan 2021	IOP Publishing
5	SM control system based on deep reinforcement learning (Nikolaev *et al.*, 2021)	Jun 2021	IOP Publishing
6	A bibliometric and visualized overview for the evolution of process safety and environmental protection (Xue *et al.*, 2021)	Jun 2021	MDPI AG
7	Current and future lithium-ion battery manufacturing (Liu *et al.*, 2021)	Apr 2021	Elsevier BV
8	A DL mask analysis toolset using mask SEM digital twins (Baranwal *et al.*, 2020)	Oct 2020	SPIE
9	A novel RPL-based multicast routing mechanism for wireless sensor networks (Hwang *et al.*, 2020)	Jan 2020	Inderscience Publishers (IEL)
10	A topic-based patent analytics approach for exploring technological trends in SM (Wang and Hsu, 2020)	Sep 2020	Emerald
11	Fault diagnosis of various rotating equipment using machine learning approaches-A review (Manikandan and Duraivelu, 2021)	Nov 2020	SAGE Publications
12	Visual-based defect detection and classification approaches for industrial applications—a survey (Czimmermann *et al.*, 2020)	Mar 2020	MDPI AG
13	Cyber infrastructure for the democratization of SM (Davis *et al.*, 2020)	Aug 2020	eScholarship, University of California
14	Rapid detection of fast innovation under the pressure of COVID-19 (Melluso *et al.*, 2020)	Dec 2020	Public Library of Science
15	Resource usage and performance trade-offs for machine learning models in smart environments (Preuveneers *et al.*, 2020)	Feb 2020	MDPI AG
16	Machine learning for predictive and prescriptive analytics of operational data in sm (Lepenioti *et al.*, 2020)	Apr 2020	publisher unknown
17	IoT-blockchain enabled optimized provenance system for food Industry 4.0 using advanced DL (Khan *et al.*, 2020)	May 2020	MDPI AG
18	Roadmap on multiscale materials modeling (Van Der Giessen *et al.*, 2020)	Jun 2020	IOP Publishing
19	Deep-learning-based methodology for fault diagnosis in electromechanical systems (Arellano-Espitia *et al.*, 2020)	Jul 2020	MDPI AG
20	Unlabeled far-field deeply subwavelength topological microscopy (DSTM) (Pu *et al.*, 2021)	Nov 2020	Wiley
21	A new deep transfer learning based on sparse auto-encoder for fault diagnosis (Wen *et al.*, 2019a)	Jan 2019	Institute of Electrical and Electronics Engineers
22	A general end-to-end diagnosis framework for manufacturing systems (Yuan *et al.*, 2020)	Nov 2019	Oxford University Press
23	A new ensemble residual convolutional neural network for remaining useful life estimation (Wen *et al.*, 2019b)	Jan 2019	American Institute of Mathematical Sciences

(*continued*)

Table 1.
Brief bibliography information of the published papers on DL and SM (WoS)

No.	Title	Date	Publisher
24	Enhanced data-driven fault diagnosis for machines with small and unbalanced data based on variational auto-encoder (Zhao *et al.*, 2020)	Dec 2019	IOP Publishing
25	A negative correlation ensemble transfer learning method for fault diagnosis based on convolutional neural network (Wen *et al.*, 2019c)	Jan 2019	American Institute of Mathematical Sciences
26	Deep heterogeneous GRU model for predictive analytics in SM: Application to tool wear prediction (Wang *et al.*, 2019a, b)	Oct 2019	Elsevier BV
27	A transfer convolutional neural network for fault diagnosis based on resnet-50 (Wen *et al.*, 2020)	Feb 2019	Springer Nature
28	A digital-twin-assisted fault diagnosis using deep transfer learning (Xu *et al.*, 2019)	Jan 2019	Institute of Electrical and Electronics Engineers
29	A standardized PMML format for representing convolutional neural networks with application to defect detection (Ferguson *et al.*, 2019)	Jan 2019	publisher unknown
30	A negative correlation ensemble transfer learning method for fault diagnosis based on convolutional neural network (Wen *et al.*, 2019c)	Jan 2019	American Institute of Mathematical Sciences
31	Machine vision intelligence for product defect inspection based on DL and Hough transform (Wang *et al.*, 2019a, b)	Apr 2019	MDPI, Science DIrect
32	Long short-term memory for machine remaining life prediction (Zhang *et al.*, 2018)	Jul 2018	Elsevier BV
33	A new convolutional neural network-based data-driven fault diagnosis method (Wen *et al.*, 2018)	Jul 2018	Institute of Electrical and Electronics Engineers
34	DL for SM: Methods and applications (Wang *et al.*, 2018)	Jul 2018	Elsevier BV
35	Survey of advances and challenges in intelligent autonomy for distributed cyber-physical systems (Mckee *et al.*, 2018)	Jun 2018	Institution of Engineering and Technology
36	Design of DL on intelligent leveling system for Industry 4.0 technology (Tsai and Chang, 2018)	Jan 2018	EDP Sciences
37	Cloud computing resource scheduling and a survey of its evolutionary approaches (Zhan *et al.*, 2015)	Jul 2015	Association for Computing Machinery

Table 1.

Main objective of the study	To indicate of the thematic and conceptual relationship in published papers in deep learning (DL) and smart manufacturing (SM)
Statistical society	All the published paper in the WoS indexed journals in field of DL and SM
Collection data tools	Exporting data from WoS based on the research objective

Table 2.
A methodological overview of the present study

The Pearson correlation coefficient shows the correlation between a pair of recurring thematic categories of WoS-derived articles in the DL and SM field. The correlation coefficient is calculated by comparing the relative frequencies of the thematic categories (relative to each part of the input text data). A coefficient approaching 1 indicates that the values are positively correlated. Coefficients approaching zero show a negative correlation. This Pearson correlation value is calculated by the simple regression class of the Apache Math Commons library.

4. Findings

The findings presented in the following are based on the objectives in four sections: main thematic categories associated with SM in the scientific papers with focus on thematic

	Specific research objectives	Tools	Techniques
1	To analyze the main thematic categories associated with SM in the scientific papers (WoS) with emphasis on *thematic interaction*	WoS analysis tools	- Descriptive statistics - Export to Excel/CSV formats to import Voyant
2	To analyze the main thematic categories associated with DL in the scientific papers (WoS) with emphasis on *thematic interaction*	WoS analysis tools	- Descriptive statistics Export to Excel/CSV formats to import Voyant
3	To analyze the main thematic categories associated with DL and SM in the scientific papers (WoS) with emphasis on *thematic interaction*	Voyant tools	- Converting Excel output from WoS extracted categories to TXT - Several levels data cleaning to prepare Voyant input data - Text mining, graph mining, classification
4	To present a general knowledge map on the *concept interaction* in the field of DL and SM	Yewno tool	Knowledge map, graph mining

Table 3.
Data analysis tools in the present study based on the specific research objectives

interaction, main thematic categories associated with DL in the scientific papers with emphasis on thematic interaction, the main thematic categories associated with DL and SM in the scientific papers with focus on thematic interaction and a knowledge map of the concept interaction of publications in the field of DL and SM.

4.1 Smart manufacturing (SM)

Objective 1: To analyze the main thematic categories associated with SM in the scientific papers with focus on thematic interaction.

In SM, 436 papers were retrieved. The findings show that there are 43 WoS thematic categories for these papers. More than five papers are published in 25 thematic categories. These 25 WoS's thematic categories, respectively, are as follows: Engineering manufacturing, engineering electrical electronic, engineering industrial, automation control systems, computer science AI, computer science information systems, engineering mechanical, computer science interdisciplinary applications, materials science multidisciplinary, operations research management science, telecommunications, computer science theory methods, engineering multidisciplinary, physics applied, robotics, instruments instrumentation, optics, green sustainable science technology, engineering chemical, business, management, computer science software engineering, nanoscience nanotechnology, computer science cybernetics and computer science hardware architecture (Table 4). The table shows that engineering manufacturing with 28.211% and computer science hardware architecture with 1.376% have the most and most minor papers in SM.

The following cirrus provided a thematic category cloud view of the most frequently occurring main thematic categories in the papers. It provides a convenient (though reductive) overview of the papers (Figure 1).

The following trends show a line graph of the relative frequencies across the main thematic category of the papers (Figure 2). The five classes were observed in the main thematic categories of the papers (Figure 2). The most common thematic categories in these classes are engineering manufacturing, computer science information systems, engineering electrical electronic, engineering industrial and automation control systems, respectively.

Class 1: There is a thematic interaction between engineering manufacturing and engineering electrical electronic in SM,

WoS thematic categories	Paper count	% of 436
Engineering manufacturing	123	28.211
Engineering electrical electronic	84	19.266
Engineering industrial	72	16.514
Automation control systems	57	13.073
Computer science artificial intelligence	46	10.550
Computer science information systems	44	10.092
Engineering mechanical	41	9.404
Computer science interdisciplinary applications	38	8.716
Materials science multidisciplinary	38	8.716
Operations research management science	37	8.486
Telecommunications	30	6.881
Computer science theory methods	29	6.651
Engineering multidisciplinary	23	5.275
Physics applied	20	4.587
Robotics	18	4.128
Instruments instrumentation	17	3.899
Optics	17	3.899
Green sustainable science technology	15	3.440
Engineering chemical	14	3.211
Business	11	2.523
Management	10	2.294
Computer science software engineering	8	1.835
Nanoscience nanotechnology	7	1.606
Computer science cybernetics	6	1.376
Computer science hardware architecture	6	1.376

Table 4.
WoS thematic categories in SM

Figure 1.
Thematic category cloud view of the most frequently occurring main categories in the field of SM

Class 2: There is not any thematic interaction between engineering electrical electronic and other thematic categories in SM,

Class 3: There is a thematic interaction between engineering industrial and engineering electrical electronic in SM,

Class 4: There is a thematic interaction between automation control systems and engineering industrial in SM and

Class 5: There is not any thematic interaction between computer science information systems and other thematic categories in SM.

Table 5 shows the subject relative between every main thematic category and SM. It is found that engineering manufacturing has maximum relation with SM. Engineering mechanical has minimum relation with SM.

Asemi and Ko (2019) determined the co-occurrence and clustering of the keywords in SM. The researchers have a focus on "Flow control," "Embedded systems," "Internet of Things (IoT)," "Big data" and "Cyber physical system" in this area. This cluster has very close relation with third and fifth cluster in the first level of the research (MP4 1).

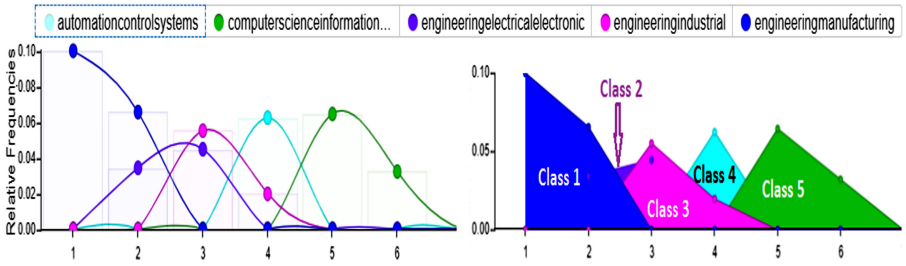

Figure 2.
Relative frequencies across the main thematic categories of the papers and thematic interaction between them in SM

Category	Subject relative
Engineering manufacturing	165,625
Computer science information systems	96,875
Engineering electrical electronic	79,167
Engineering industrial	75,000
Automation control systems	62,500
Computer science artificial intelligence	52,083
Computer science interdisciplinary	46,875
Materials science multidisciplinary	45,833
Operations research management science	45,833
Telecommunications	38,542
Computer science theory methods	30,208
Engineering multidisciplinary	28,125
Physics applied	28,125
Robotics	22,917
Instruments instrumentation	20,833
Optics	20,833
Engineering chemical	16,667
Green sustainable science technology	16,667
Business	12,500
Management	10,417
Computer	8,333
Science software engineering	8,333
Nanoscience nanotechnology	7,292
Computer science cybernetics	6,250
Computer science hardware architecture	6,250
Engineering mechanical	1,042

Table 5.
Subject relative between every main thematic category and SM

https://www.researchgate.net/publication/353692404_AsemiKo-OGIK09-Clustering_all_Keywords_L2-20-12-2019mp4.

Data/Mp4 1. Clustering all keywords in SM (Asemi and Ko, 2019)

4.2 Deep learning (DL)

Objective 2: To analyze the main thematic categories associated with DL in the scientific papers with emphasis on thematic interaction.

In DL, 9119 papers were retrieved. The findings show that there are 190 WoS thematic categories for these papers. More than 135 papers are published in 25 thematic categories. These 25 WoS's thematic categories, respectively, are as follows: Engineering electrical electronic, computer science artificial intelligence, computer science theory methods, computer science information systems, telecommunications, computer science, interdisciplinary applications, radiology nuclear medicine medical imaging, imaging science photographic technology, computer science software engineering, optics, automation control systems, engineering biomedical, computer science hardware architecture, robotics, mathematical computational biology, education educational research, multidisciplinary sciences, remote sensing, acoustics, neurosciences, biochemical research methods, medical informatics, instruments instrumentation, transportation science technology and physics applied (Table 6). The table shows that engineering electrical electronic with 31.352% and physics applied with 1.513% have the most and least papers in DL.

The following cirrus provided a thematic category cloud view of the most frequently occurring main thematic categories in the papers. It provides a convenient (though reductive) overview of the papers (Figure 3).

Table 6. WoS Thematic categories in DL

WoS thematic categories	Paper count	% of 9,119
Engineering electrical electronic	2,859	31.352
Computer science artificial intelligence	2,441	26.768
Computer science theory methods	1,379	15.122
Computer science information systems	1,181	12.951
Telecommunications	702	7.698
Computer science interdisciplinary applications	700	7.676
Radiology nuclear medicine medical imaging	613	6.722
Imaging science photographic technology	529	5.801
Computer science software engineering	450	4.935
Optics	398	4.365
Automation control systems	391	4.288
Engineering biomedical	377	4.134
Computer science hardware architecture	332	3.641
Robotics	319	3.498
Mathematical computational biology	269	2.950
Education educational research	238	2.610
Multidisciplinary sciences	224	2.456
Remote sensing	222	2.434
Acoustics	190	2.084
Neurosciences	186	2.040
Biochemical research methods	171	1.875
Medical informatics	148	1.623
Instruments instrumentation	142	1.557
Transportation science technology	140	1.535
Physics applied	138	1.513

The following trends show a line graph of the relative frequencies across the main thematic category of the papers (Figure 4). The five classes were observed in the main thematic categories of the papers (Figure 4). The most common thematic categories in these classes are engineering electrical electronic, computer science artificial intelligence, computer science theory methods, computer science information systems and computer science interdisciplinary applications, respectively.

Class 1: There is a thematic interaction between computer science information systems and computer science artificial intelligence in DL,

Class 2: There is not any thematic interaction between computer science artificial intelligence and other thematic categories in DL,

Class 3: There is not any thematic interaction between computer science theory methods and other thematic categories in DL,

Class 4: There is a thematic interaction between engineering electrical electronics and computer science theory methods in DL,

Class 5: There is not any thematic interaction between computer science interdisciplinary applications and other thematic categories in DL.

Table 7 shows the subject relative between every main thematic category and DL. It is found that engineering manufacturing has maximum relation with DL. Engineering mechanical has minimum relation with DL.

4.3 Deep learning and smart manufacturing (DL and SM)

Objective 3: To analyze the main thematic categories associated with DL and SM in the scientific papers with an emphasis on thematic interaction.

In DL and SM, three papers were retrieved. The findings show that there are ten WoS thematic categories for these papers. The WoS thematic categories, respectively, are as follows: Computer science, engineering, operation research management science, automation control system and metallurgy metallurgical engineering (Figure 5).

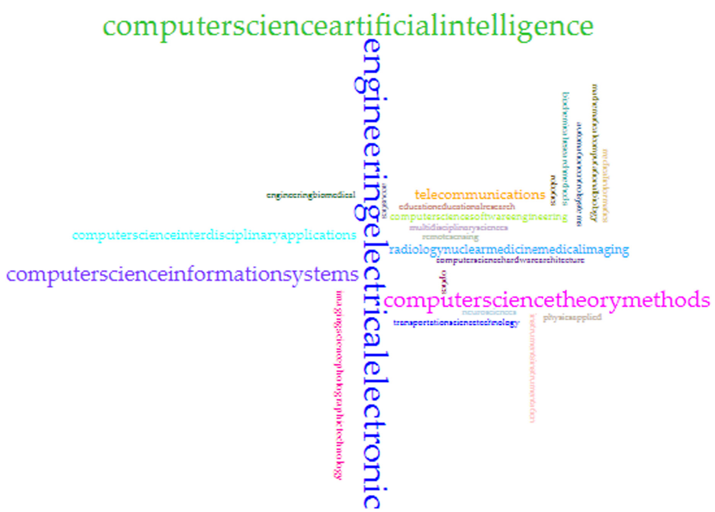

Figure 3.
Thematic category cloud view of the most frequently occurring main categories in DL

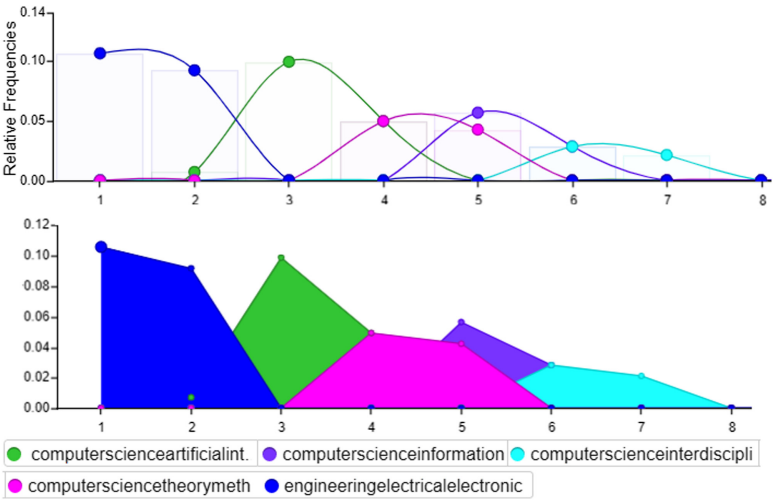

Figure 4.
Relative frequencies across the main thematic categories of the papers and thematic interaction between them in DL

Category	Subject relative
Engineering electrical electronic	197,183
Computer science artificial intelligence	154,930
Computer science theory methods	91,549
Computer science informotion systems	84,507
Computers cience interdisciplinary applications	49,296
Telecommunications	49,296
Radiology nuclear medicine medical imaging	42,254
Computer science software engineering	35,211
Imaging science photographic technology	35,211
Automation control systems	28,169
Engineering biomedical	28,169
Optics	28,169
Computer science hardware architecture	21,127
Mathematical computational biology	21,127
Robotics	21,127
Acoustics	14,085
Biochemical research methods	14,085
Education educational research	14,085
Multidisciplinary sciences	14,085
Neurosciences	14,085
Remotesensing	14,085
Instruments instrumentation	7,042
Medical informatics	7,042
Physics applied	7,042
Transportation science technology	7,042

Table 7.
Subject relative between every main thematic category and DL

The following cirrus provided a thematic category cloud view of the most frequently occurring main thematic categories in the papers. It provides a convenient (though reductive) overview of the papers (Figure 6).

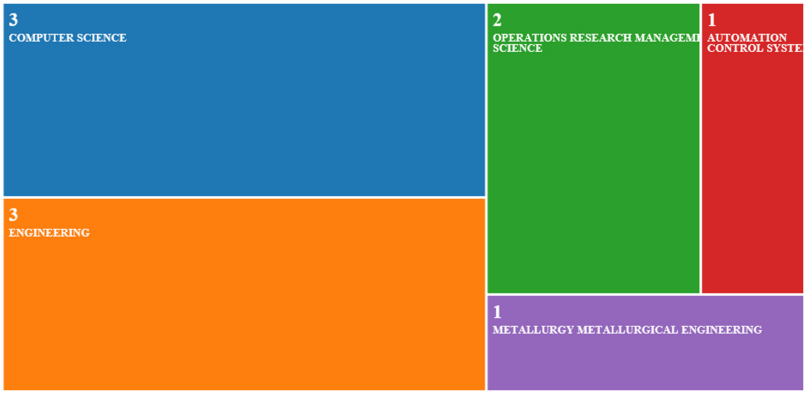

Figure 5.
WoS thematic categories in DL and SM

The following trends show a line graph of the relative frequencies across the main thematic category of the papers (Figure 7). The most common thematic categories in these classes are computer science, engineering, operation research management science, automation control system and metallurgy metallurgical engineering, respectively.

Figure 8 shows the subject correlation and significance between two main thematic categories in DL and SM. It is found that there is nohigh significance correlation between every two main thematic categories in DL and SM.

This is a measure of the significance of the correlation value. Often a significance of 0.05 or less indicates a strong correlation. We typically have a small number of values, so this value should be used with care. There is a measure of how closely thematic categories correlate (using Pearson's correlation coefficient or simple regression.

4.4 Knowledge map of the concept interaction of publications in DL and SM

In this section, using the Yewno tool, we extracted a knowledge map and concept interaction between unstructured and structured data on the DL and SM concepts (Figure 9). The Yewno tool is inspired by how information is processed from multiple sensory channels and uses advanced computational linguistics, network theory, machine learning and classical AI methods (Yewno, Inc., 2020). The findings explored 16 concepts via mapping knowledge of DL and SM. This map shows that concepts such as feature learning, AI, supervised learning, convolutional neural network, speech Hochreiter, speech recognition, artificial neural network and its types, vanishing gradient problem and restricted Boltzmann machine have direct interaction with DL and machine learning. Their interaction with SM is indirect and by dealing with machine learning. The concepts such as supply network, database, financial performance and energy consumption are in indirect interaction with machine learning by dealing with DL too.

5. Discussion and conclusion

By reviewing the scientific production of DL and SM, we can show the general state of scientific production in this area and its growth trend. Researchers who intend to conduct studies in DL and SM can, based on the results of the thematic interactions obtained from this study, create better ideas for their research, while better understanding the issues. During the study, the thematic categories that are neglected and in which fields of study are not identified as missing circles in this field are discovered and researchers can focus their studies

Figure 6.
Thematic category cloud view of the most frequently occurring main categories in DL and SM

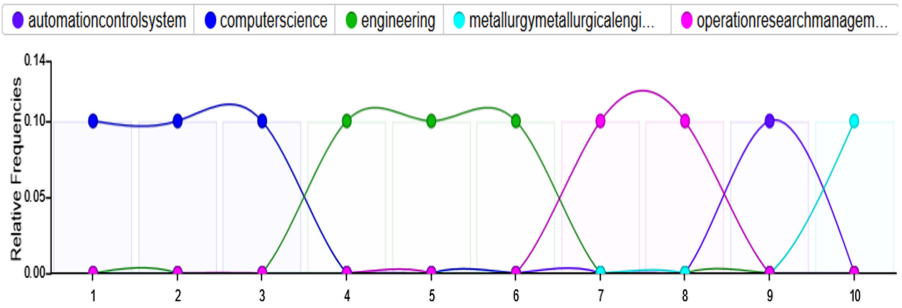

Figure 7.
Relative frequencies across the main thematic categories of the papers and thematic interaction between them in DL and SM

Category 1	←	→	Category 2	Correlation (r)	Significance (p)
computerscience			operationresearchmanagementscience	−0.32732683	0.35588378
engineering			operationresearchmanagementscience	−0.32732683	0.35588378
computerscience			engineering	−0.42857143	0.21654728

Figure 8.
Subject correlation and significance between two main thematic categories in DL and SM

on those areas. Given the importance of DL and SM in scientific production, attention to studies in this area is important. The study of thematic or thematic categories of scientific products in this field and their interactions with other thematic areas can be of great help to policymakers, officials and planners of research. They can better manage financial capital and research budgets and identify research priorities. By reviewing the thematic categories of scientific publications, the DL and SM field can draw a scientific map of this area and present it through previous studies in a comprehensible form in this subject area. The results of this study can provide a coherent and well-mapped road map to the main policymakers of research in DL and SM, through the study of coexistence and interactions of the thematic categories with other thematic areas. The knowledge map of DL and SM concepts shows that there are currently few concepts interacting with each other while the rapid growth of technology and the needs of today's society are revealed the need to use more and more DL in SM. At present, it seems that Wen Long has published most of the papers in DL and SM. As

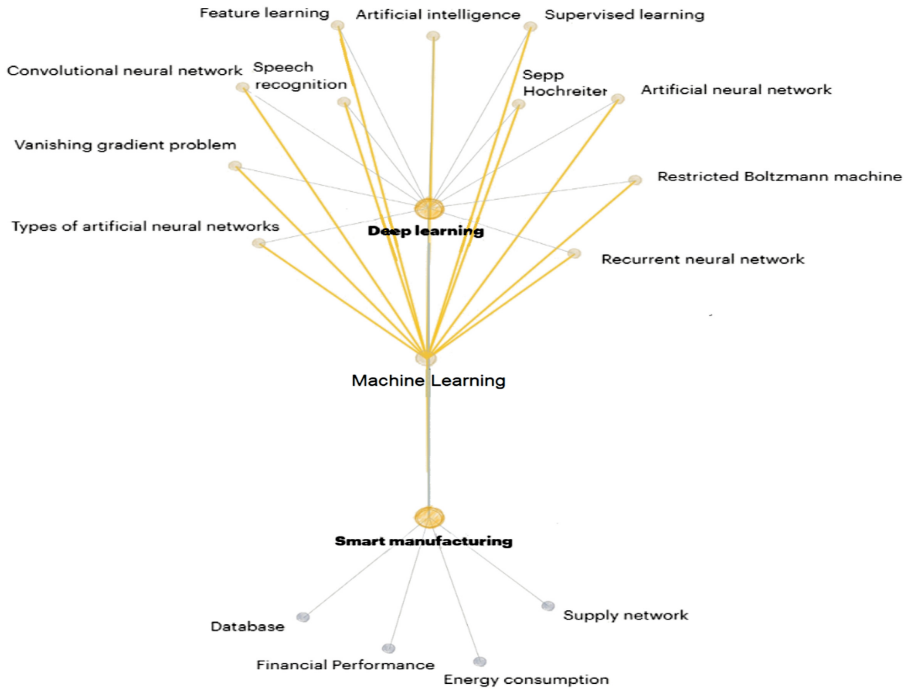

Figure 9.
Subject correlation knowledge map of the concept interaction in DL and SM

mentioned, SM involves the production of a group of products that use an advanced level of intelligent technology in the production process. The use of DL combined with rapid design changes and digital information technology has a great impact on an important part of intelligent production. The results show that not much research has been done in this area. The SM industry is expanding day by day. There is an urgent need to use AI techniques, such as machine learning techniques in the SM process. DL can be used to improve SM in some important parts of production. Selection of the proper machine learning techniques for different purpose in manufacturing improves the SM industry. In selection of proper technique, the first step is studding about the capability, strengths and limitations of techniques. DL is a most recent machine learning technique; however, it is more suitable for image processing purpose in SM. If we choose the DL for any recognition purpose, then we increase the complexity of manufacturing systems where other machine learning techniques with lower complexity such as reinforcement learning (RL) method would be more suitable. Even in the smart supply chain, which is a subset of SM, using fuzzy techniques for multiple attribute decision-makings is more effective in comparison with machine learning techniques. Currently, limited work has been done in this area. By designing production processes based on DL, we can help people to have a better life. Good solutions can be provided for optimal decision-making in various dimensions of SM using neural networks and DL. According to analysed data and findings, it can be concluded that the application of DL in SM based on industrial AI is considered by the researchers. This means that the application of DL in IoT-based SM is not considered by the authors. This could be a field that has the potential to conduct extensive research in this area. The results also show that another case that has the potential to conduct research on the application of DL in SM is deep RL. This area, which includes more topics of AI, in the process of SM allows manufacturers to interact deeply with

the dynamic environment around them to achieve their goals. Thus, to make the best decision, the ideal behavior in a particular field of evaluation is done in depth. With the help of DL-based feedback, machines can learn behavior in depth and improve it in the long run. These feedbacks are considered a reinforcing signal. In this way, they can design more effective guidelines and strategies to solve the problems of researchers in conducting their studies and direct the scientific production of researchers in this field.

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