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REVIEW

Mapping Digitalization in Smart and Sustainable Agricultural Mechanical Systems

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Abstract: This study examines the growth of digitalization in smart and sustainable agricultural mechanical systems using bibliometric methods. Data were retrieved from Web of Science (368 records) and Scopus (310 records). After this step, 94 duplicate documents were removed, leaving 584 documents for the period from 2000 to 2025 for analysis. The number of publications has grown steadily since 2018 and is expected to reach over 100 records in 2024. The dataset had an annual growth rate of 14.31%, an average of 10.06 citations per document, and 317 contributing sources. Keyword co-occurrence analysis identified the main topic groups related to "IoT," "intelligent systems," "sustainable development," "Industry 4.0," "artificial intelligence," and "Industry 5.0." The outcomes show a shift from individual technical solutions to networked fields of research in the digitalization of mechanical systems and sustainability. The main links were found among Internet of Things, artificial intelligence, Industry 4.0, Industry 5.0, and sustainability. This study contributes to the literature through a three-layer keyword strategy related to digitalization, smart sustainability, and agricultural machinery. This approach will help future interdisciplinary studies define clearer directions for research in this field.

Keywords: digitalization, technology, sustainability, agricultural, mechanical systems

1. Introduction

Digital transformation has become more prevalent in research and practice in engineering, agriculture, and production systems [1, 2]. This trend is also evident in mechanical engineering and technical systems, including applications in agriculture [3]. In this context, smart agri-mechanical systems are not restricted to machine operation or technical design. Concepts such as the Internet of Things (IoT), cyber-physical systems (CPS), artificial intelligence (AI), and smart manufacturing now support the development of smart agricultural machinery [4]. These technologies also link the performance of the machinery to energy consumption, resource efficiency, and environmental management [5].

Furthermore, recent bibliometric studies have targeted research streams that are related but not analyzed in unison. One stream concentrates on digital transformation in the agriculture sector [6]. Another recent study on agrifood systems covers the role of sustainability transitions in this research field [7, 8]. In addition, a bibliometric study of IoT applications in agricultural research has been conducted [9]. These studies provide useful evidence for each direction of research. However, they continue to focus on a variety of themes, including digital agriculture, IoT applications, and sustainability transitions. Still, less attention has been paid to how smart technologies and sustainability goals jointly shape agricultural mechanical systems [10]. This study attempts to fill this gap by using a three-layered keyword strategy. This design helps to explore the current interdisciplinary structure of digital transformation in agricultural machinery.

This research landscape that is highly fragmented and in need of a knowledge map. Research initiatives range from the design, control, and optimization of industrial processes to circular economy, sustainable development, Industry 4.0, and Industry 5.0 [11]. However, these themes are frequently addressed separately and not as interrelated components of smart and sustainable agri-mechanical systems [12]. This diversity raises the need for an overall picture to systematize research directions and identify convergence points and unexploited gaps.

Therefore, the use of scientific data analysis methods such as bibliometrics is appropriate for this study. Through the synthesis and processing of data from international databases, this bibliometric review describes the publication trends in the field of digitalization and intelligent mechanical systems in agriculture [9]. It also clarifies prominent key phrases that reflect a shift in academic interests [13]. The analysis reveals key topic areas and their relationship with digital transformation, smart production, and sustainability agendas [14].

Based on this, the study has three specific objectives that together constitute its main contributions. First, it describes the academic landscape of digitalization and intelligent mechanical systems in agriculture [6], including the data scale and prominent research trends [15]. Second, it identifies and explains topic clusters to provide insights into the interrelationship between

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technological aspects and sustainability goals [16, 17]. Third, it addresses the implications of the results for industry development, research planning, and training in this field [18].

Thus, this study goes beyond data description by offering a reference framework for scientists, engineers, and policymakers to determine future priorities for the digitalization of agri-mechanical systems [19]. Additionally, the results emphasize the role of digital transformation in building intelligent agricultural mechanical systems. This is reflected in the application of smart technologies that link production efficiency to sustainability targets. These elements are the main contributions of this bibliometric analysis.

2. Literature Review

Digital technologies are now being used in agricultural production to link data from the field, machines, and control functions within operational systems [20]. This relationship is explained from the perspective of cyber-physical systems, which connect computation algorithms with physical systems and digital representations, such as digital twins [21]. The topic has evolved to become more interdisciplinary over time and has intersected with production and sustainability studies. The cyber-physical systems perspective explains how sensors, data, and physical machines connect to form digitally connected systems. The sustainability transitions perspective is useful in understanding why production systems transition toward energy efficiency, circularity, and greener operations [22, 23]. These changes are related to machinery, skills, organizational routines, and industrial contexts through a socio-technical systems perspective [24]. Together, these perspectives guide the discussion on relationships between digital technologies, sustainability targets, and agricultural mechanical systems. Thus, digital technologies are the enabling domain, and smart agri-mechanical systems are the transformation processes. Bibliometric mapping illustrates the outcome area via sustainability targets, publication patterns, and keyword links.

2.1. The role of digital transformation in smart and sustainable agri-mechanical systems

Digitalization is the transformation of the entire system design, management, and operation into digital technology. Unlike digitization, which only stops at digitizing data, digitalization is associated with creating a new operating model in which data are connected and processed intelligently [25, 26]. In the mechanical field, including applications in agriculture, this concept is often associated with the IoT, physical systems, cyberspace, AI, or big data analysis [21, 27]. These types of technologies assist in creating intelligent technologies that can monitor and optimize themselves [28, 29].

In fact, digital transformation has brought many obvious applications to the mechanical industry [30]. The use of digital simulation in product design processes has allowed for the reduction of testing time and mistakes [31]. Predictive analytics tools can also enhance operations and maintenance, with AI-driven crop monitoring supporting precision agriculture and sustainability efforts [31, 32]. Similarly, smart production lines use digital technology to coordinate machines, which saves costs and enhances accuracy [33]. These changes not only bring about economic efficiency but also enable greater flexibility, helping mechanical systems in agriculture to become better adapted to today's competitive environment [34, 35].

In addition, digital transformation links technological change with broader sustainability transitions in production systems [22]. Optimizing processes using real-time data helps reduce energy consumption, limit material waste, and extend product life cycles [36]. Models such as the "digital twin" also help businesses control environmental impacts from the design stage, instead of just processing at the final stage [37, 38]. Therefore, digitalization is not only about technical innovation but also a tool to support the realization of a circular economy and green production in agricultural and industrial systems [39].

From the above analysis, it can be seen that digital transformation has become an important foundation for the development of smart and sustainable mechanical systems in agriculture [20]. However, the diversity of applications and approaches requires the systematization of research directions to identify central topics and open gaps. This content is also presented in the next subsection.

2.2. Prominent research directions in the field of digitalization and mechanical systems

In the process of developing global understanding, research on digital transformation in the field of mechanical engineering for agricultural applications has formed many different approaches [18, 40]. This diversity demonstrates the growing interest in academia and industrial practice. However, because of the many parallel research directions, this field has become complex, and it is difficult to have a clear overall landscape [11]. Classifying the literature into thematic groups will help easily identify the main characteristics and trends, thereby explaining why a systematic synthesis method is needed.

First, this research stream focuses on core technologies with practical applications in agriculture [41]. Previously, mechanical studies may have been characterized by the application of machine functions and their technical features. Today, it is increasingly connected to the Internet, sensors, and digital data systems [42]. These studies revolve around the IoT, physical systems, cyberspace, digital twins, AI, machine learning (ML), and robotics [21, 43]. The aim of this research stream is to exploit digital technology to increase connectivity, improve performance, and optimize operations [44]. Consequently, mechanical systems can be monitored in real time, predict failures, and support quick decisions [45]. This is considered a foundational research area, creating the basis for the development of other applications.

In addition, another group focuses on manufacturing and industrial models [46]. Concepts such as Industry 4.0, Industry 5.0, smart manufacturing, or automation are placed in a direct relationship with digital transformation [47, 48]. This research stream frequently examines the restructuring of production processes and the design of more flexible value chains. It also uses data to match resources within socio-technical production systems [24, 40]. A special aspect is the combination of digital technology and industrial strategy, with the aim of making the mechanical industry more competitive and flexible for agricultural applications [49].

Furthermore, growing research attention has been directed toward sustainability and circularity. The content of this group is related to sustainable production, circular economy, energy saving, or green production [50]. This direction also reflects the sustainability transitions in production systems [23]. Digital technology increases productivity, reduces emissions, manages product life cycles, and encourages environmental responsibility [36].

The three groups above reflect the multidimensional development of the field of digitalization in mechanics. However, there is a limitation in that no research is sufficient to systematize all trends. Therefore, the application of bibliometric analysis is necessary to build a knowledge map, pointing out the central topics and open gaps. This is also the basis for the current research, which is developed in the next section. To better understand research streams, contributions, and gaps, an analytical comparison of previous studies is included in Appendix C.

3. Methodological Framework

A systematic bibliometric-text mining paradigm was used in this study to map the intellectual field of digitalization of smart and sustainable agri-mechanical systems. The general flow of the analysis can be seen in Appendix B.

3.1. Research design overview

This study follows a five-stage workflow for connecting data retrieval, bibliometric mapping, and text mining in one design. This logic is based on accepted methodological frameworks in science. For example, in spatial data processing, the acquisition, preprocessing, network construction, visualization, and interpretation are defined as sequential steps [51]. Specifically, the process starts with the layering of the construction of keywords. This was followed by the retrieval of records from bibliographic databases and preprocessing for a consistent corpus for analysis.

Next, the study creates bibliometric structural maps through complementary relational views. The conceptual structure is explored in terms of keyword co-occurrence and co-word relations, as topic linkages are represented in author terms and indexing terms [52, 53]. The intellectual structure is interpreted based on citation-based linkages. In this approach, bibliographic coupling is used to record common reference databases and co-citation to establish patterns of following citations in the referenced publications [54, 55]. In order to improve cluster interpretability, a text-based enhancement step was used to extract key phrases. Subsequently, the robustness was evaluated by comparing it to popular topic-modeling approaches and performing overlap tests [53].

3.2. Data acquisition and preprocessing

3.2.1. Keyword layer construction

To ensure that the collected data fully reflect the research topic, the keyword identification process was conducted based on the title and purpose of the topic. The keywords were divided into three classes, which helped narrow the search scope and limit the possibility of missing relevant documents.

First, the keyword layer of "digitalization" and "informatics" is considered the main axis because it is directly linked to the study's objective. This group includes concepts like "digitalization," "digital transformation," "informatics," and "information systems," along with familiar Industry 4.0 terms including "cyber-physical systems" and "Internet of Things (IoT)" [56]. This is the foundation for identifying the development of digital transformation in mechanics [57].

Second, the keyword layers of "smart" and "sustainable" were used to ensure that the research scope was always linked to smart and sustainable elements [33]. Keywords such as "sustainability," "sustainable development," "smart systems," "intelligent systems," or "green technology," and "eco-efficiency" help to link digitalization with the goal of long-term and environmentally friendly development [58].

Finally, the mechanical systems keyword layer plays a role in maintaining the specificity of the mechanical engineering industry, particularly in agricultural applications [56]. This layer includes the phrases "mechanical systems," "mechanical engineering," "mechanical design," "engineering systems," and "agricultural mechanical" [59]. As a result, the collected data remain close to the research focus, avoiding spreading to less relevant fields.

3.2.2. Search protocol and data retrieval

The search and data collection processes were carried out on two international databases: Web of Science (WoS) and Scopus [60]. WoS and Scopus were chosen because they offer standardized records that are acceptable for use with Bibliometrix and VOSviewer. These databases were chosen because they provide structured bibliographic metadata and citation information, which are needed to enable reproducible bibliometric analysis. Other platforms also exhibit less consistent metadata and duplicate control and citation coverage, and they don't offer DOI fields, abstracts, author keywords, or stable export formats. Data merging and duplicate screening were supported by their combined use to support the study design. A set of keywords was built based on the three previously defined layers and then combined into a common search syntax [61]. This syntax uses logical operators to link terms on digitalization, smart and sustainable, and mechanical systems to broaden and concentrate the search [62].

The search syntax used was as follows: ("digitalization" OR "digitalization" OR "digital transformation" OR "informatics" OR "information systems" OR "Industry 4.0" OR "cyber physical systems" OR "IoT") AND ("sustainability" OR "sustainable development" OR "sustainable systems" OR "smart systems" OR "intelligent systems" OR "green technology" OR "eco-efficiency") AND ("mechanical systems" OR "mechanical engineering" OR "mechanical design" OR "engineering systems" OR "agricultural mechanical" OR "agriculture"). In this phase, Scopus and WoS yielded 310 documents and 368 records, respectively. After pooling and deduplication, a total of 94 records were removed. This resulted in a final dataset of 584 records for bibliometric analysis. Combining two databases with three in-depth analytical stages allows for cross-checking of the findings and increases the strength of the conclusions [63].

3.2.3. Dataset merging and deduplication

After pooling the two databases, records exported in BibTeX format (.bib) were imported into R using convert2df(). The argument dbsource was set to match the database origins. The structure was matched to the export structure using the parameter format = "bibtex."

The two source data frames were then merged using mergeDbSources(Mwos, Mscopus, remove.duplicated = TRUE). During the process of being removed.duplicated = TRUE, similar data across the entire merging process were removed by finding similar fields on tags between the sources. In cases where there is a valid identifier, duplicate screening gives preference to the DOI. Title information is used when the information on the DOI fields is nonexistent or incongruent to identify redundant documents [64].

Using this procedure, 94 duplicate records were removed. The resulting dataset consisted of 584 distinct documents that were further analyzed in terms of bibliometry.

3.3. Bibliometric network construction

After data cleaning, the bibliometric analysis was performed in three analytical directions in order to represent both the performance characteristics and knowledge structure.

3.3.1. Descriptive performance analysis

Descriptive performance indicators were calculated using the Bibliometrix package to characterize the corpus and offer context for the science mapping later in the analysis. The final dataset consisted of 584 documents published between the years 2000–2025, retrieved from WoS (n = 368) and Scopus (n = 310) after removing 94 duplicates, and which are distributed across 317 sources. The annual growth rate of the corpus is 14.31%, the average age of the document is 4.66 years, and the average number of citations per document is 10.06 [65].

To describe the topical coverage and collaboration patterns, results were presented in terms of keywords and authorship statistics [66]. The dataset contained 2115 Keywords Plus and 3293 author keywords with 1868 authors and 3.49 co-authors per document, as well as 12.84% international co-authorships. Document types were also summarized to clarify the evidence base and included articles (n = 134), proceedings papers (n = 247), conference papers (n = 96), and reviews (n = 36). This study follows a bibliometric workflow that consists of several clear steps, as summarized in Appendix B.

3.3.2. Co-occurrence network analysis

VOSviewer was used to construct and visualize a keyword co-occurrence network based on author keywords. Author keywords were extracted and standardized using term normalization and synonym harmonization (e.g., "IoT" and "Internet of Things"). The co-occurrence map was created based on a minimum occurrence threshold of five.

The similarity between keywords i and j was calculated as $s\_ij = c\_ij/(w\_i \text{ x } w\_j)$. Here, c_ij represents the number of co-occurrences of keywords i and j, and w_i and w_j represent the marginal frequencies of each keyword. This normalization is useful for VOS mapping in placing the keywords that are strongly related to each other closer by utilizing a weighted distance-based objective [51]. For this study, the higher the value of normalized similarity, the stronger the conceptual relationship between two keywords in the mapped network.

Clusters were automatically generated in VOSviewer and then interpreted using standard map attributes. Node size is dependent on the frequency of the keywords, and link thickness is dependent on the strength of the association.

3.3.3. Thematic mapping and structural evolution

The structure and development of the field were examined using thematic mapping implemented in the Bibliometrix R package. Themes were identified from author-keyword co-occurrence clusters and placed on a strategic diagram based on centrality and density measures [53]. In this approach, centrality is the degree of the connection of a theme with other themes, while density is the degree of internal cohesion of keywords in the same theme [52]. Centrality was calculated as $c = 10 \times \Sigma$ e_kh, where k is a keyword that is in the theme and h is a keyword that is out of the theme. Density was computed as $d = 100 \times (\Sigma$ e_ij/w), where i and j are keywords within the theme and w is the number of keywords in that theme [53]. Accordingly, centrality was used to measure external links, and density was used to measure the internal development of each theme. Based on these indices, clusters were classified into motor, basic, niche, and emerging/declining themes using the standard quadrant interpretation of the strategic diagram.

In order to follow the structural evolution over time, ggplot2 was employed to visualize the distribution and shift through time of the author keywords across the study period. The resulting thematic clusters were interpreted using core topical axes. These axes were in line with previous field syntheses and covered digitalization, Industry 4.0, AI, digital twins, and sustainable production [46, 67].

3.4. Text mining enhancement layer

The research involved a text-based method by which important phrases from the texts in the articles were retrieved to make theme interpretation more transparent [68]. This step was conducted after the bibliometric analyses using the same merged and cleaned dataset from Scopus and WoS. Rather than being another analytical framework, it was a layer that provided interpretation and validation [64].

Standard preprocessing procedures were applied. These included lowercasing, stop word removal, and normalization of terms through lemmatization. All text processing and keyword extraction steps were performed in the R environment using established text mining and data manipulation packages [69].

3.4.1. TF–IDF weighting

Keywords were extracted using the term frequency–inverse document frequency (TF–IDF) weighting, and the top-ranked terms were retained as candidates [70]. This weighting method assigns greater weights to terms that are common in a document but rare in the whole document collection [71]. In this study, TF–IDF was used to identify terms that were specific to certain documents but not overly common across the entire corpus. For a term t in document d, TF–IDF is computed as tfidf(t,d) = tf(t,d) $\times$ idf(t), where tf(t,d) is the term frequency in document d. The inverse document frequency is calculated as idf(t) = ln(N/df(t)), where N is the total number of documents and df(t) is the number of documents containing t.

3.4.2. Validation procedure

An evaluation protocol, consisting of three steps, was used to validate the existence of coherence between TF–IDF signals and bibliometric patterns [53]. First, descriptive convergence was considered by comparing the extracted term set (T) with the author's keyword set (K). The overlap ratio was defined as $|T \cap K| / |T|$ and $J = |T \cap K| / |T \cup K|$ was used as a robustness check using Jaccard similarity [72]. A higher value indicates a stronger overlap between the extracted terms and the author keywords.

Second, structural consistency was evaluated by the association of extracted terms with keyword co-occurrence clusters using VOSviewer. Each word was assigned to the cluster in which it had a proportion of the highest proportion of related author keywords. The assignment relied on co-occurrence relations from the network built with a minimum occurrence threshold of five [51].

Third, highly ranked TF–IDF terms that failed the threshold were treated as cross-cutting terms. The labels of these clusters were refined and used to interpret the clusters thematically in Bibliometrix [64].

3.5. Robustness and validation strategy

A benchmark check was performed based on an existing topic-modeling technique. Latent Dirichlet allocation (LDA) was selected because it represents each document as a mixture of latent topics, while each topic is a probability distribution over words [73]. This process provides a second and different perspective on the prevailing themes using the same title and abstract corpus [74].

The details of the benchmark implementation were provided to facilitate replication and comparison between the runs. The parameters included the number of topics (K = 5), the inference algorithm (Gibbs sampling), and training parameters (burn-in = 1000, iterations = 2000, thinning = 100, seed = 2025). K = 5 was chosen because it reflects the co-occurrence structure of keywords and ensures the comparison is interpreted. To estimate the latent topic patterns in the title and abstract corpus, Gibbs sampling was used. A fixed seed was used for reproducibility and to minimize the variance between replicate runs. These settings allowed for comparisons between LDA topics and TF–IDF terms and keyword clusters [73]. Parameter sensitivity was considered as the topic number, and prior settings could alter topic separation and word overlap [74]. The quality of the model was verified using standard topic evaluation signals. Coherence was used as an indicator of interpretability, while perplexity was used as an indicator of statistical fit, although the two measures do not necessarily align. The comparison between the benchmark outputs and the TF–IDF term list was used to evaluate the stability of the dominant themes. The measure of stability was the level of similarity between the top m topic words and top m TF–IDF terms, and the results were illustrated in terms of $J = |A \cap B| / |A \cup B|$ [75]. This comparison improves interpretive transparency, since dominant themes are supported under an alternative text-based model. The proposed bibliometric mapping outputs are consistent with the intended scope of the analysis.

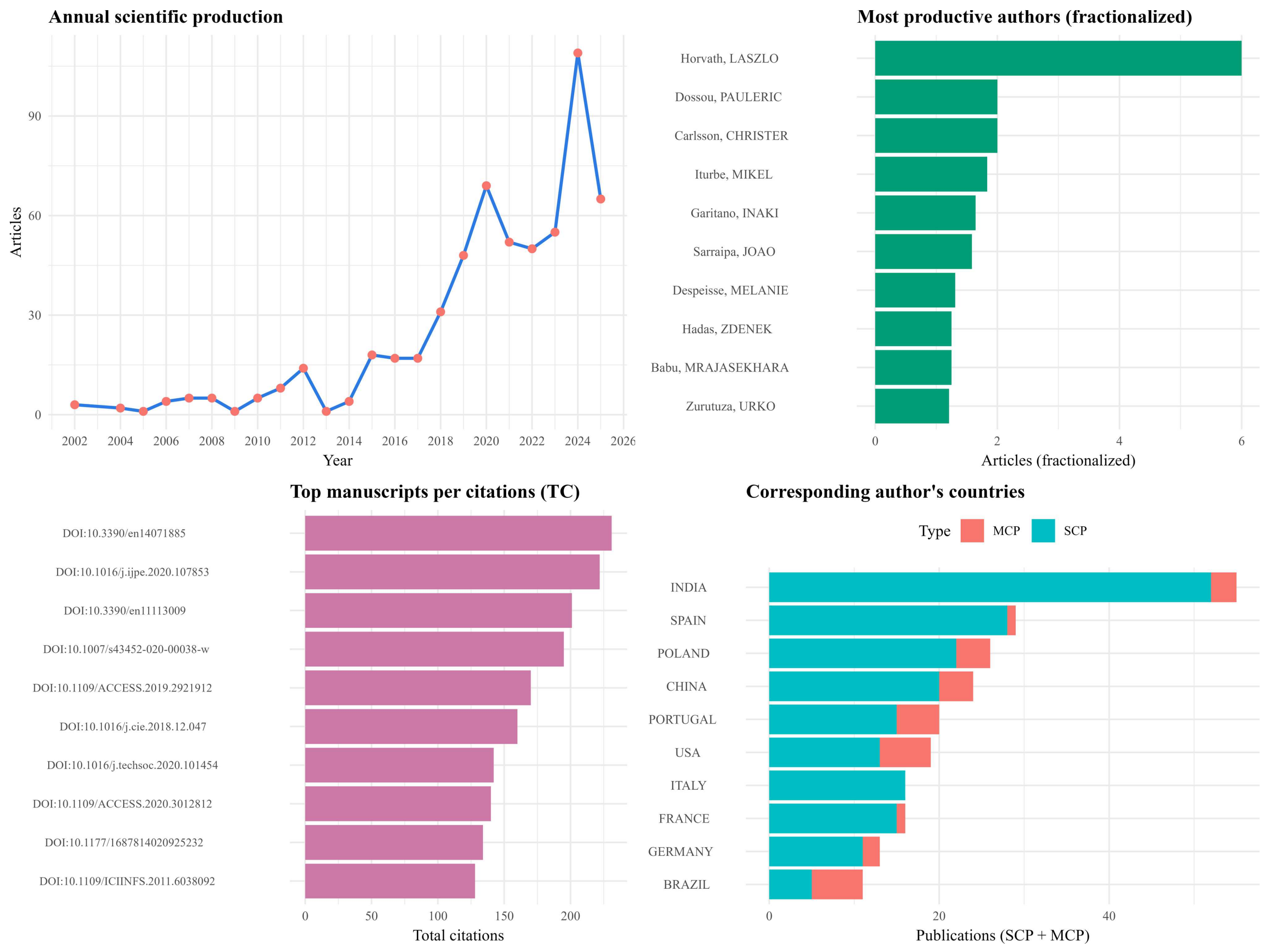
4. Results

4.1. Dataset information

Table A1 and Figure 1 provide a general overview of the research dataset. They provide publication trends, contributing authors, most-cited publications, and country distributions.

Figure 1 shows the rapid growth of this research field over the past two decades. From 2002 to 2012, the number of publications per year was limited, fluctuating in the single digits. However, from 2013 onward, the growth rate became clear and reached a leap between the period 2018 and 2025. In 2024, more than 100 articles were published, reflecting the growing interest of the academic community in the topic of digitalization in smart and sustainable mechanical systems [76]. This trend is in line with the context of

Figure 1
Scientific output and research impact in the dataset



Industry 4.0 and green transformation, which is being strongly promoted globally.

When looking at the authors, the results show that the research in this field is scattered. Notable authors such as Horvath Laszlo, Dossou Paltieric, Carlsson Christer, and Iturbe Mikel have only about 3–5 publications. This shows that there is no leading group of authors, but instead, many scholars from different countries contribute. This reflects the interdisciplinary nature and expansion of the topic, where many research groups develop in parallel [77].

The list of the most-cited articles reveals that influential works often appear in prestigious journals such as *Energies*, *Journal of Cleaner Production*, and *International Journal of Production Economics*. The leading article has more than 200 citations, confirming the impact of studies linking digitalization to production and sustainability [13]. This proves that the field is growing rapidly in quantity and creating highly influential research.

In terms of countries, India has the largest number of publications, mostly in the form of single-country collaborations. In contrast, global academic interdependence is reflected in a higher share of international cooperation in Spain, China, Portugal, and the United States. The diversity of nations and cooperation imply that digitalization in mechanical engineering may have diverse researchers from many different situations and perspectives.

4.2. Text-derived keyword patterns and validation results

First, Table A2 reports TF–IDF terms extracted from titles and abstracts across the corpus [70]. Several top items reflect an engineering and production discourse, including "engineer" (TF–IDF = 6.053; DF = 169) and "manufacture" (6.004; 183). In parallel, industrial framing remains dominant, with "industry" (5.292; 282) and "industrial" (4.923; 281) appearing often.

Moreover, technology-oriented terms indicate sustained interest in intelligent industrial systems, including "smart" (4.504; 159), "digital" (4.347; 132), "IoT" (4.197; 149), and "intelligent" (4.134; 140). Meanwhile, implementation themes are visible through "process" (4.122; 262), "design" (4.028; 193), and "management" (3.972; 139). Alongside these patterns, "technology" shows the widest reach (3.678; 303), while "sustainable" (3.947; 178) and "development" (3.545; 214) suggest an applied sustainability framing. Notably, "datum" (5.000; 224) also ranks highly, reflecting broad reporting language in abstracts [70].

Next, Table A3 indicates strong convergence between automated extraction and author keywords, with an overlap rate of 70%, which supports the interpretability of text-derived terms as thematic indicators [78, 79]. In addition, eight extracted terms map to co-occurrence clusters, supporting the alignment with the bibliometric structure. However, 22 unmapped terms function as cross-cutting concepts that traverse cluster boundaries, helping to capture integrative signals beyond cluster-specific keywords. Where topic modeling is used as a benchmark, stability can be examined by comparing topic outputs with the TF–IDF list [80].

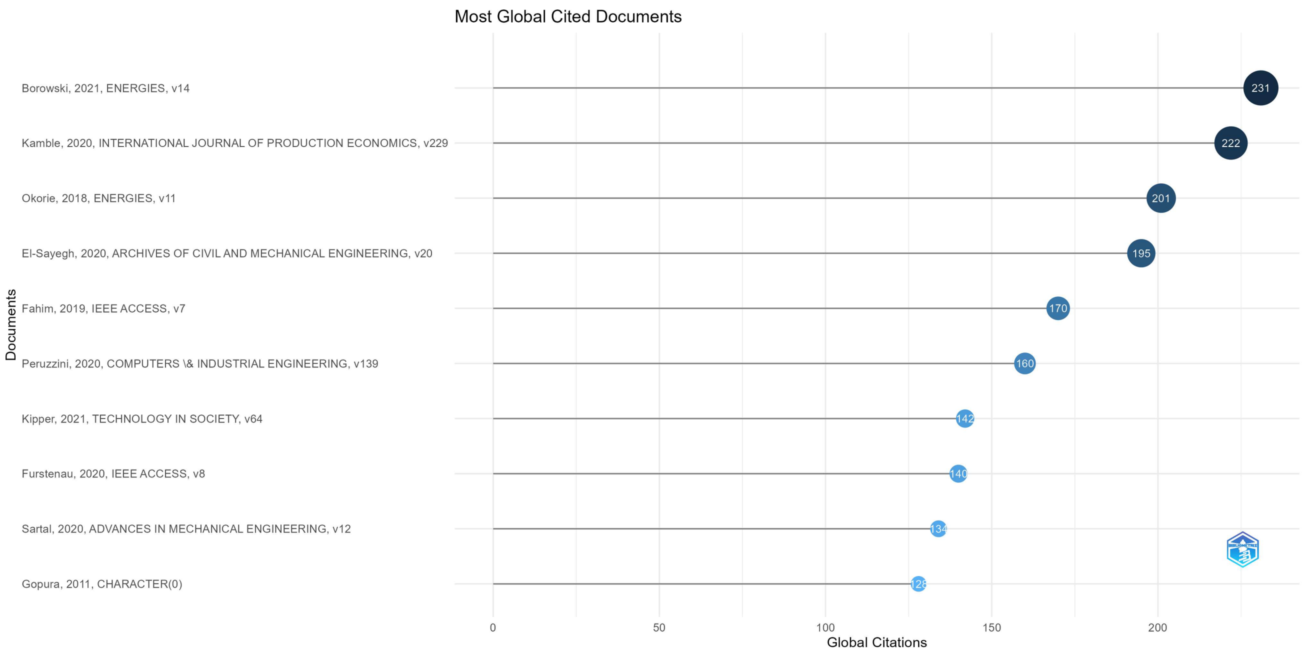
4.3. Top 10 authors with cited documents

An analysis of the top citation lists revealed some of the most influential papers in the fields of digitalization and engineering. As shown in Figure 2 and detailed in Table A4, the top 10 papers all have over 100 citations, with some exceeding 200 citations.

Figure 2 presents the 10 most-cited publications, which reflect the most prominent digitalization research in the fields of mechanics and sustainability. In particular, Borowski's study (2021, *Energies*) has 231 citations, averaging 46.2 citations per year. The standardized total cited index (14.54) further shows that this study immediately gained academic attention and was utilized as a key reference [76].

The next most-cited study was published in the *International Journal of Production Economics*, with 222 citations, averaging 37 per year. The research presented here focuses on production management in Industry 4.0, reflecting the growing interest

Figure 2
Most documents' global citations



in digitalization and value chain optimization [77]. In addition, two works published in *Energies* and *Archives of Civil and Mechanical Engineering* have 201 and 195 citations, respectively. These publications significantly contribute to the enhancement of the theoretical framework surrounding sustainable energy and mechanization [13].

Other IEEE Access research includes IoT anomaly detection and prediction strategies, showing how data analytics and AI can be used to design smart and secure mechanical systems [81]. However, Peruzzini (2020, *Computers & Industrial Engineering*) and Kipper (2021, *Technology in Society*) both achieved over 140 citations, focusing on the application of digital technology in intelligent systems and engineering management [25, 34]. Despite the limited time spent on publication, these works still attained a high citation rate, which is a trend in the field. Finally, studies published in 2020 broadened the scope of the discussion by linking sustainability with Industry 4.0, addressing both technical and socio-technological perspectives [28].

This knowledge of the problem confirms the centrality of digitalization in manufacturing and mechanics and expands into energy, management, and sustainable development research. This is an important reference for analyzing academic trends in the future.

4.4. Analysis results from the co-occurrence

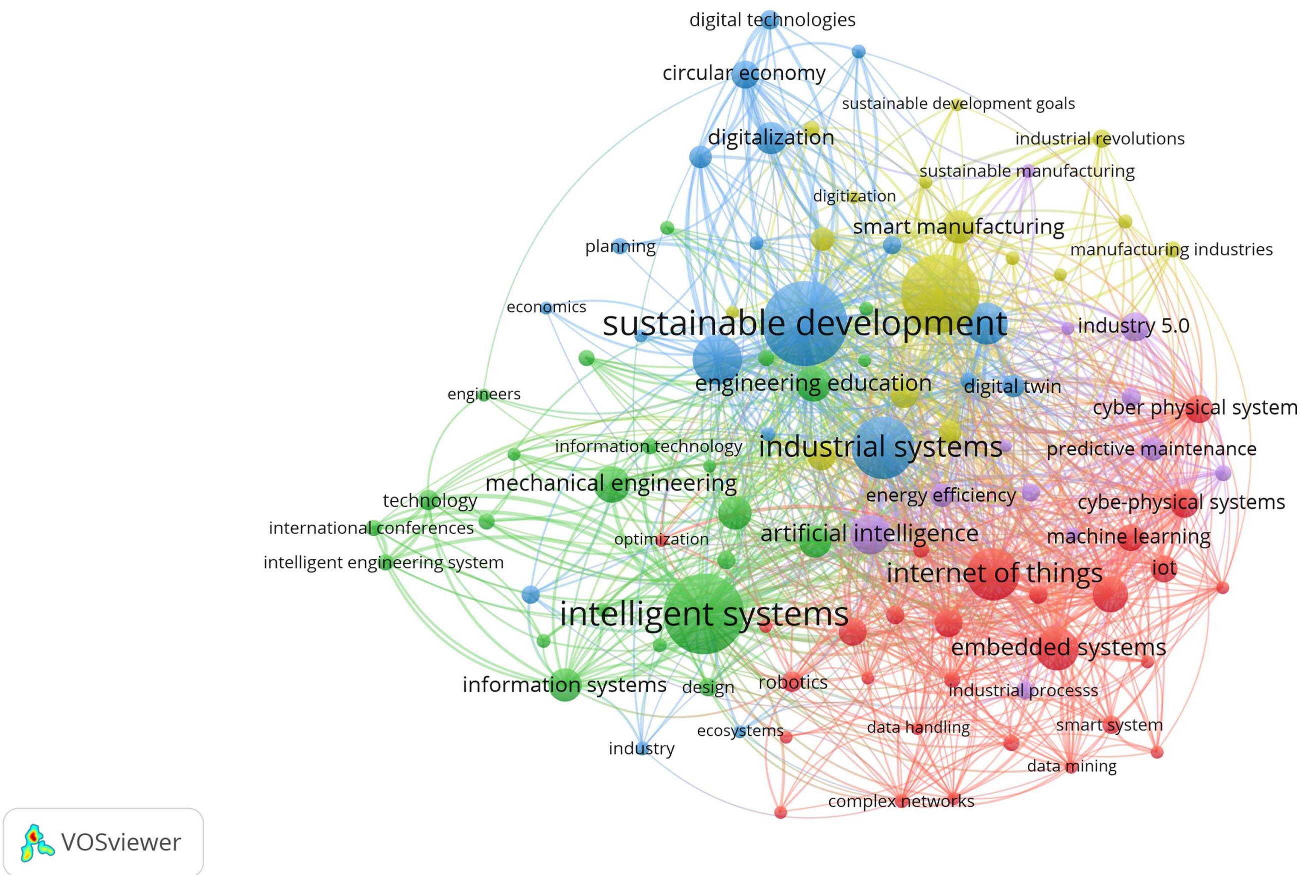
Keyword co-occurrence analysis is one of the important tools to explore the underlying knowledge structure in a research field. By determining the frequency and relationship between keywords, this method allows for the identification of central topics, closely related clusters of concepts, and shifts in approach over time. The analysis results in Table A5 and Figure 3 show the prominent keywords by cluster.

Figure 3 shows a visualization of keywords divided into five clusters, each with links to form its own specific content group.

In the first cluster, the metrics measure the degree of connection between keywords in the knowledge network according to their occurrences and total link strengths. The keyword with a strong link to "IoT" (37, 205) reflects its connection with related terms in the field of smart mechanical devices and systems [82]. Related keywords such as "cyber-physical systems" (21, 151), "embedded systems" (28, 179), and "machine learning" (14, 71) show the integration between digital infrastructure and ML algorithms. Simultaneously, "robotics" (10, 51) and "decisionmaking" (15, 94) extend the application to automation and management support [83]. Overall, this cluster represents the core technology platform of the connected systems.

Next, the second cluster focuses on "intelligent systems" (34, 169) along with "engineering education" (18, 96), "information systems" (20, 112), and "knowledge management" (15, 87). This is a group of keywords that reflects the role of intelligent systems in training and management environments. Here, the integration of digitalization serves production and contributes to the formation of human resources and the improvement of management efficiency [84]. The highlight is the connection between mechanical engineering and technical education and information

Figure 3
Co-occurrence map of keywords in digitalization and mechanical systems



management, demonstrating a clear interdisciplinary nature [85]. This connection is also the foundation for linking digitalization with sustainable development, as emphasized in the third cluster.

In the third cluster, "sustainable development" stands out with 73 occurrences and 365 link strengths, acting as a bridge between technology and sustainability goals [45]. Accompanying keywords such as "circular economy" (21, 128), "digital twin" (17, 103), "blockchain" (12, 91), and "supply chains" (19, 116) show a broader scope of digitalization. These keywords suggest that digitalization extends beyond engineering and into industrial management and value chains [86]. This cluster reflects the global trend of combining digital technology with the green economy, toward circular production and efficient use of resources [87]. From this point, research continues to develop toward Industry 4.0, smart manufacturing, automation, and process optimization.

In the fourth cluster, "Industry 4.0" plays a central role with 65 occurrences and 339 link strengths, confirming it as the main axis of the field [88]. Related keywords such as "smart manufacturing" (27, 147), "automation" (22, 134), "life cycle" (16, 89), and "digital transformation" (18, 101) describe the shift from traditional production models to smart manufacturing, where digitalization becomes the main driving force [89]. This cluster shows that digitalization is not only a technology trend but also a production and business strategy associated with process innovation and operational optimization.

Finally, the fifth cluster emphasizes the role of "artificial intelligence" (29, 158) along with "Industry 5.0" (14, 73), "predictive maintenance" (12, 65), "sustainable manufacturing" (19, 101), and "green manufacturing" (15, 92). The following keywords demonstrate the growing use of AI to improve maintenance, reduce costs, and shift to green manufacturing [90]. The combination of Industry 5.0 and AI technology opens up a new vision, in which people, machines, and environmental factors are harmoniously integrated [28, 91].

Thus, while the first cluster focuses on the technology platform, the last cluster suggests a future development direction, comprehensively connecting three axes: mechanics, digitalization, and sustainability.

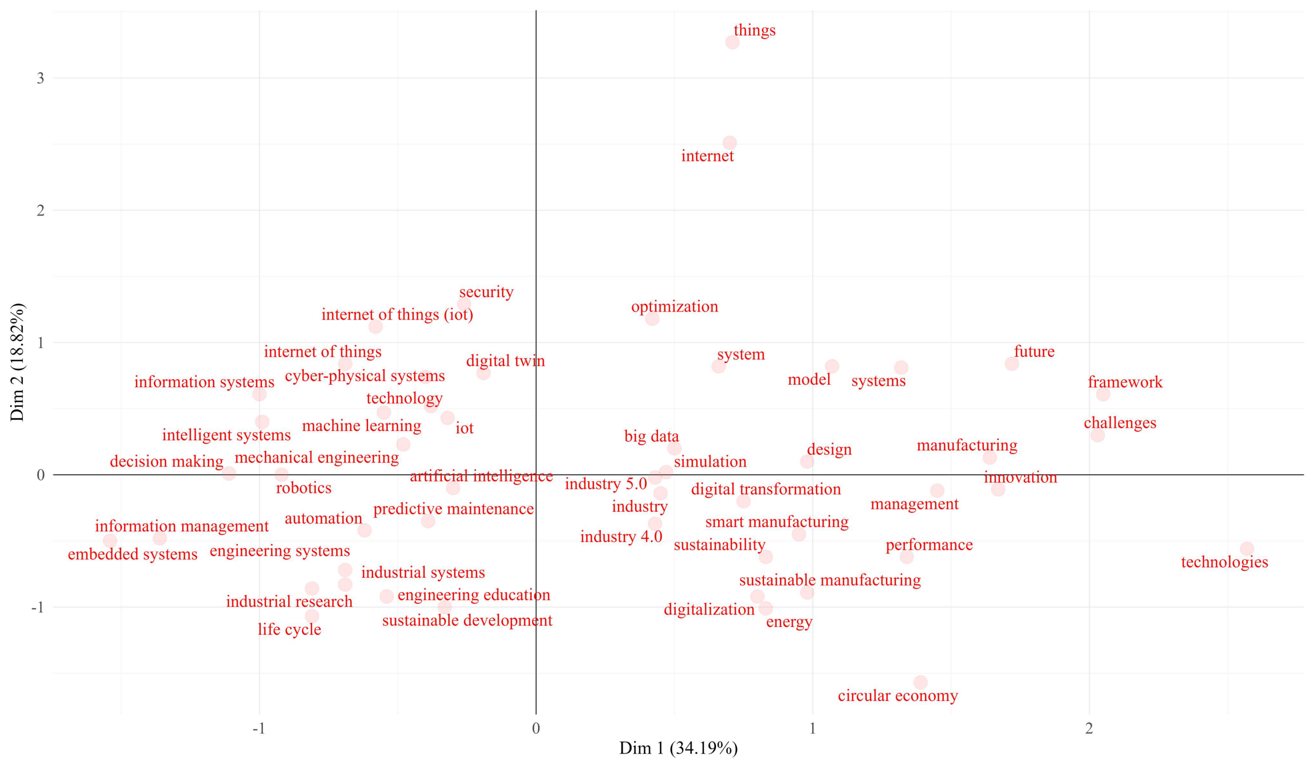
4.5. Thematic analysis of research domains

The results of the thematic map analysis are presented in Figure 4 and detailed in Table A6. These results allow the knowledge structure of the research field to be divided into four groups. These groups include basic, motor, niche topics, and emerging topics. This distribution helps clarify the role of each keyword phrase and shows the central content axis and potential research directions for future studies.

Figure 4 presents the results of the keyword analysis in two-dimensional maps (Dim1 and Dim2), thereby identifying four thematic clusters. This grouping visualizes conceptual proximity, directions of major research, and areas for future expansion.

The first cluster focuses on keywords such as "internet of things" (−0.69, 0.84), "IoT" (−0.32, 0.43), "cyber-physical systems" (−0.40, 0.74), "intelligent systems" (−0.99, 0.40), and "machine learning" (−0.55, 0.47). This cluster is a core technology platform, with IoT as the central connectivity layer. Physical, cyber, and AI systems offer data analysis and processing capabilities [59]. This linkage shows the formation of a smart ecosystem, which is becoming the infrastructure for many industrial applications and services [47]. This cluster indicates a transition from devices to connected technical systems. It also reveals that data-based control is becoming mainstream in agricultural machinery.

Figure 4
Thematic map of keyword clusters



The second cluster includes the keywords “sustainability” (0.83, −0.62), “sustainable development” (−0.33, −1.00), “digitalization” (0.80, −0.92), “circular economy” (1.39, −1.57), and “energy” (0.83, −1.01). This research area connects digitalization with sustainability goals, from energy optimization to building a circular economy model [13]. The location of the keywords on the map shows that this orientation is not only linked to the theory of sustainable development but also opens up opportunities to apply digital technology to minimize environmental impact. This cluster reveals that system design is increasingly associated with sustainability [36]. This also suggests that digital tools are employed to enable resource efficiency.

The third cluster is highlighted by the keywords “management” (1.45, −0.12), “design” (0.98, 0.10), “manufacturing” (1.64, 0.13), “smart manufacturing” (0.95, −0.45), and “performance” (1.34, −0.62). This theme emphasizes the application of IoT and digital technology in improving management processes, product design, and production operations [77]. The keyword “innovation” (1.67, −0.11) further indicates that innovation is associated with this cluster. This reflects the strong development of Industry 4.0 toward flexible and efficient production models [34]. This cluster shows a stronger linkage between technical design and production management. It also shows the role of digitalization in manufacturing systems in terms of operations [92].

The last cluster is represented by keywords such as “framework” (2.05, 0.61), “future” (1.72, 0.84), “systems” (1.32, 0.81), “optimization” (0.42, 1.18), and “technologies” (2.57, −0.56). This is a future-oriented research group that focuses on building conceptual frameworks, models, and overall solutions [57]. The prominent position of the keyword “technologies” shows the role of expanding beyond the scope of a single IoT, moving toward multidisciplinary integration. This emphasizes the shift from core technology research to the development of systems for long-term development [88]. This cluster represents the need for more models than just single-technology applications. It also outlines future research on integrated systems and cross-sector solutions.

Thus, the thematic analysis from co-occurrence not only helps to identify four main research clusters, including IoT technology, sustainable development, management and smart manufacturing, and future-oriented framework. It also explains the interdisciplinary links in smart and sustainable agricultural mechanical systems [93]. This result provides a scientific basis for scholars to position their work in the overall picture and orient subsequent research according to global trends. Overall, the clusters illustrate the increasing interconnections between digitalization, production, and sustainability. The thematic clusters also indicate a trend shift in agricultural mechanical research from individual technical functions to system design. Data control, sustainability requirements, production management, and system planning are the main areas linked to smart machinery in thematic clusters.

5. Discussion

The results suggest a change in the use of isolated technologies to a smart digital ecosystem in agricultural machinery. In this ecosystem, IoT, CPS, AI, and data analytics work together. These elements are also increasingly in line with sustainability and circularity. Accordingly, the co-occurrence network and thematic map outline “who studies what” in this field. They also demonstrate the development of technology, production, and sustainability together over time.

Simultaneously, the conceptual counterpart of the bibliometric framework was acquired through text-based keyword extraction. Several high-ranking terms are used as cross-cutting concepts across more than one cluster. They were not combined into a single coherent theme in the keyword structure. Terms like “digital,” “smart,” “industrial,” and “sustainable” are used to present connections between technological, organizational, and sustainability-oriented discussions throughout the literature. Thus, in the future, these general drivers may be used together with cluster-specific themes to understand intelligent industrial development.

First, the technology platform cluster (IoT, CPS, AI, and ML) highlights a major development direction in the field. It focuses on connectivity and data processing capabilities from a cyber-physical systems perspective [21, 94]. IoT has a position to determine the connection axis, while CPS, AI, and ML are responsible for analysis and decision-making [95]. Therefore, it was upgraded from discrete systems to a service-oriented intelligent architecture for mechanics and production lines [96]. Moreover, this structure operates as an infrastructure for industrial applications, from monitoring and predictive maintenance to coordination of human and equipment tasks in factories. The current mapping has a greater mechanical system focus than bibliometric reviews on digital agriculture [6]. This study bridges the gap between earlier studies on IoT in sensing and connectivity and CPS and AI in production line coordination [9]. This comparison implies that the digitalization in agri-mechanical systems is not limited to the adoption of technologies at the farm level [97].

Second, in the sustainability and circular economy cluster, sustainability is no longer a stand-alone topic. It is closely linked to the digital change and sustainability transitions of production systems [22, 23]. The terms life-cycle traceability, energy optimization, and circular design are supported by twin, blockchain, and sensor data [98]. Themes related to digitalization include efficiency and environmental impact reduction for green manufacturing and life-cycle management. The cluster is different from the bibliometric studies on IoT in that it also covers sensing and connectivity, CPS, and AI [9]. It also builds on recent field syntheses and links digitalization with smart production and sustainability [46].

Third, the group of applications in systems, administration, design, and smart manufacturing suggests a change in enterprise operation. Companies are transitioning from local-level optimization to data-based operations management [31]. This system integrates performance measurement functions, predictive maintenance, and Operator 4.0 interfaces, making the process more flexible and accurate [89]. Consequently, innovation is no longer considered an “output” of the chain but becomes a permanent operating mechanism, aiming at a lean model and performance optimization. This cluster shifts the focus from general production management to agri-mechanical operations by studying the application of Industry 4.0 [77].

Fourth, the theme clusters indicate that conceptual frameworks, future visions, and interdisciplinarity have become key research concerns. This focus shifts from basic technology to more complex challenges of intellectual and transdisciplinary importance. In contrast, this method emphasizes system structure and integration plan between humans, machines, and the environment [39]. The move toward Industry 5.0 with emphasis on humanistic and environmental values is displayed in this development [88, 99]. Optimization methods and simulation systems are essential for increasing system flexibility and extending applications to new industrial areas [90]. This cluster is related to Industry

5.0-oriented work and links human-centered values with future agri-mechanical system design [100].

Therefore, the central theme of the period 2018–2025 is smart digital ecosystems with sustainability goals. Digital infrastructure allows for data and analytical capabilities, and supply chain management and sustainability principles are embedded into system design. The dataset contains high-impact works consistent with this development. They refer to the co-evolution of digitalization, operational optimization, and environmental goals [76].

Furthermore, the results contribute perspectives on the relationship between social and technical infrastructure in line with the socio-technical systems perspective [24]. Digital infrastructure groups are intermediaries between design, mechanical construction, and sustainability effects. These contributions explain why the keywords twin, chain traceability, and life-cycle management moved from the "niche" to "motor" on the topic map [13, 37]. Meanwhile, the Industry 5.0 axis indicates that the human-centered school does not replace Industry 4.0. Rather, it provides humanistic and green perspectives on the ecosystem structure [40, 46].

However, this study had several methodological limitations. The dataset was retrieved from the WoS and Scopus databases. There is a possibility that some documents have been overlooked due to the use of British or American spelling, narrow industry terminology, or less standardized document titles. Furthermore, bibliometric outcomes rely on the coverage of the database, search terms, quality of indexing, and number of citations over time. Keyword co-occurrence and citation counts can reveal research trends but cannot substantiate causal relationships and effectiveness in practice [66]. Co-occurrence maps may emphasize highly frequent terms, and emerging topics may be underrepresented because of the gradual growth of citations. Network boundaries are determined by thresholds, keyword cleaning, and synonym choices, rather than fixed topics. Thus, the findings should be considered as evidence for the knowledge structure rather than a direct demonstration of technical performance. Accordingly, future studies should include systematic reviews or expert Delphi studies for each subsector [101]. However, there is a need for empirical sector-specific studies in the energy, machine manufacturing, and construction sectors. These studies explore the impact of digital capabilities on environmental indicators and specialized chain performance [102].

Overall, three main insights are presented in this study. First, the field has shifted from broad topics related to digitalization to a focus on integrated frameworks relating IoT and intelligent systems and sustainability issues. Second, the thematic map shows a definite progression of the basic themes to more advanced clusters, implying the rapid development of the structure. Third, the co-occurrence map reveals the emerging impact of Industry 5.0 and digital twins, which has not been mapped in previous reviews.

6. Conclusion and Implementation

The research results clearly depict the development of digitalization in smart and sustainable agricultural mechanical systems. They show a shift from individual technology models to integrated ecosystems of IoT, AI, and CPS. Keyword co-occurrence analysis shows the topics being reported by the studies. These topics include digital technology platforms such as IoT, CPS, AI, and ML. They also involve concepts of sustainable development, circular economy, smart governance, manufacturing, and theoretical approaches for future research. This formation and distribution process demonstrates the merging of technological innovation and sustainability objectives. In particular, automation, real-time data, and digital design have become key issues in the mechanical industry transformation.

On the academic front, this study adds empirical evidence of the convergence of technology and sustainable development. This convergence reflects a shift on the technical level and also reformulates the field of industrial management research. Through bibliographic analysis, this study reinforces the argument that digitalization is no longer a supporting factor. Instead, mechanical research gives rise to smart, industrial ecosystems of data, automation, and AI that drive value creation [103]. Moreover, the results contribute to the understanding of the academically organized field. They also help researchers identify directions across various subfields of mechanics, energy, and construction. This is especially relevant for smart and sustainable agricultural mechanical systems. These issues are symbiotic and are strongly influenced by Industry 4.0 and 5.0 trends.

From an application perspective, it is found that different priorities are required for agricultural machinery companies, farms, cooperatives, and training organizations. Machinery companies should embed IoT sensors into tractors, harvesters, irrigation machinery, and post-harvest machinery [104]. These sensors can monitor the performance of such machines, fuel usage, field conditions, and maintenance requirements. AI can assist in irrigation and fertilization scheduling, support weed detection, identify pests, and monitor crops, benefiting both cooperatives and farms [105]. This aligns with smart agriculture, in which connected and data-driven farming systems are enabled by the IoT, robotics, AI, and blockchain [56]. Digital twins and edge computing can help agricultural equipment managers monitor energy consumption, predict equipment failures, and reduce emissions. For instance, sensor dashboards can be more directly linked with data from machinery, maintenance planning, and farm decisions. In cooperative operations, AI modules can assist with irrigation scheduling, pest recognition, and weed detection. However, digital transformation in agriculture also raises ethical and sustainability issues. Energy use and electronic waste, as well as data privacy, platform dependency, and digital skills, should also be considered during implementation. Such concerns indicate the need for technical investments and responsible governance in smart agricultural mechanical systems [97]. Moreover, governments and training bodies should facilitate the transfer of knowledge through digital means and cross-sectoral skills development. These technical workers should be trained in the use of sensors, machine diagnosis, reading data, and making basic decisions based on AI. These efforts can help technical workers adapt to the green transition.

Future research should focus on motor themes within the four identified thematic clusters. The themes included digitalization, sustainability, and circular economy. In the future, studies should be expanded to other specific sectors, such as energy, manufacturing, construction, and agricultural machinery. Empirical studies are needed to test the impact of digital infrastructure on energy usage, emissions, maintenance costs, and production performance. Future research is also needed to develop life-cycle-based indicators to assess smart agri-mechanical systems throughout design, operation, and disposal. Case studies can be used to explore issues such as data interoperability, AI governance, digital skill gaps, and disparities between small farms and larger businesses. This direction involves linking technology, society, and environmental concerns within a single production ecosystem. Further research into data privacy, cybersecurity, technology access for small farms, and actual impacts of digital technology on the environment should also be explored [106].

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Mendeley Data at https://doi.org/10.17632/85dvr6kcxv.1.

Author Contribution Statement

Nguyen Van Ninh: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Phuong Viet Do:** Validation, Writing – review & editing.

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Appendix A

Detailed results of the bibliometric analysis

Table A1
Main information about data

Description	Results
WoS	368
Scopus	310
Number of duplicate records removed	94
Timespan	2000:2025
Sources (journals, books, etc.)	317
Documents	584
Annual growth rate %	14.31
Document average age	4.66
Average citations per doc	10.06
Keywords Plus (ID)	2115
Author's Keywords (DE)	3293
Authors	1868
Authors of single-authored docs	43
Single-authored docs	61
Co-authors per doc	3.49
International co-authorships %	12.84
Article	134
Article; book chapter	2
Article; early access	1
Book	23
Book chapter	25
Conference paper	96
Conference review	14
Editorial	3
Editorial material	1
Proceedings paper	247
Retracted	1
Review	36
Review; early access	1

Table A2
Top 20 TF–IDF keywords

Keyword	TF–IDF (sum)	Document frequency
Engineer	6.053	169
Manufacture	6.004	183
Industry	5.292	282
Datum	5.000	224
Industrial	4.923	281
Energy	4.623	112
Smart	4.504	159
Digital	4.347	132
IoT	4.197	149
Intelligent	4.134	140
Process	4.122	262
Network	4.045	133
Design	4.028	193
Management	3.972	139
Product	3.949	108
Sustainable	3.947	178
Production	3.887	163
Technology	3.678	303
Information	3.560	159
Development	3.545	214

Table A3
Keyword validation summary

Validation dimension	Result	Interpretation
Overlap with author keywords	70%	High convergence between automated extraction and author-assigned keywords
Mapped to co-occurrence clusters	8 terms	Text-derived keywords align with bibliometric cluster structure
Unmapped text-derived terms	22 terms	Cross-cutting or foundational concepts spanning multiple themes

Table A4
Authors with the highest global manuscript citations

Paper	DOI	Total citations	TC per year	Normalized TC
Borowski, 2021, Energies, v14	10.3390/en14071885	231	46.20	14.54
Kamble, 2020, International Journal of Production Economics, v229	10.1016/j.ijpe.2020.107853	222	37.00	10.12
Okorie, 2018, Energies, v11	10.3390/en11113009	201	25.13	13.12
El-Sayegh, 2020, Archives of Civil and Mechanical Engineering, v20	10.1007/s43452-020-00038-w	195	32.50	8.89
Fahim, 2019, IEEE ACCESS, v7	10.1109/ACCESS.2019.2921912	170	24.29	12.02
Peruzzini, 2020, Computers & Industrial Engineering, v139	10.1016/j.cie.2018.12.047	160	26.67	7.30
Kipper, 2021, Technology in Society, v64	10.1016/j.techsoc.2020.101454	142	28.40	8.94
Furstenau, 2020, IEEE ACCESS, v8	10.1109/ACCESS.2020.3012812	140	23.33	6.38
Sartal, 2020, Advances in Mechanical Engineering, v12	10.1177/1687814020925232	134	22.33	6.11
Gopura, 2011, Character	10.1109/ICIINFS.2011.6038092	128	8.53	5.33

Note: TC = total citations.

Table A5
Co-occurrence clusters and keyword statistics

Cluster	Keywords	Occurrences	Total link strength
Cluster 1	Internet of Things	37	205
Cluster 1	Embedded systems	28	179
Cluster 1	Cyber-physical systems	21	151
Cluster 1	Cyber-physical systems	16	120
Cluster 1	Cyber-physical system	15	120
Cluster 1	Decision-making	15	94
Cluster 1	Internet of Things (IoT)	15	67
Cluster 1	IoT	14	68
Cluster 1	Machine learning	14	71
Cluster 1	Robotics	10	51
Cluster 1	Big data	8	47
Cluster 1	Real-time systems	8	49
Cluster 1	Smart system	8	49
Cluster 1	Data acquisition	7	50
Cluster 1	Internet	7	38
Cluster 1	Machine learning	7	58
Cluster 1	Network security	7	34
Cluster 1	Complex networks	6	32
Cluster 1	Advanced analytics	5	34
Cluster 1	Data analytics	5	30
Cluster 1	Data handling	5	30
Cluster 1	Data mining	5	35
Cluster 1	Decision support systems	5	26
Cluster 1	Mems	5	20
Cluster 1	Multi-agent systems	5	20
Cluster 1	Optimization	5	27
Cluster 1	Smart systems	5	24
Cluster 2	Intelligent systems	67	263
Cluster 2	Mechanical engineering	22	69
Cluster 2	Engineering education	21	102
Cluster 2	Engineering systems	19	82
Cluster 2	Information systems	19	88
Cluster 2	Information management	18	124
Cluster 2	Technology	10	55
Cluster 2	Design	8	45
Cluster 2	Interoperability	8	42
Cluster 2	Curricula	7	35
Cluster 2	Information technology	7	49
Cluster 2	Intelligent engineering systems	7	40
Cluster 2	International conferences	7	40
Cluster 2	Management information systems	7	38
Cluster 2	Teaching	7	42
Cluster 2	Forecasting	6	31
Cluster 2	Information use	6	36
Cluster 2	Knowledge management	6	41
Cluster 2	Manufacturing	6	22
Cluster 2	Quality control	6	26
Cluster 2	Engineering research	5	26
Cluster 2	Engineers	5	23

(*Continued*)

Table A5
(*Continued*)

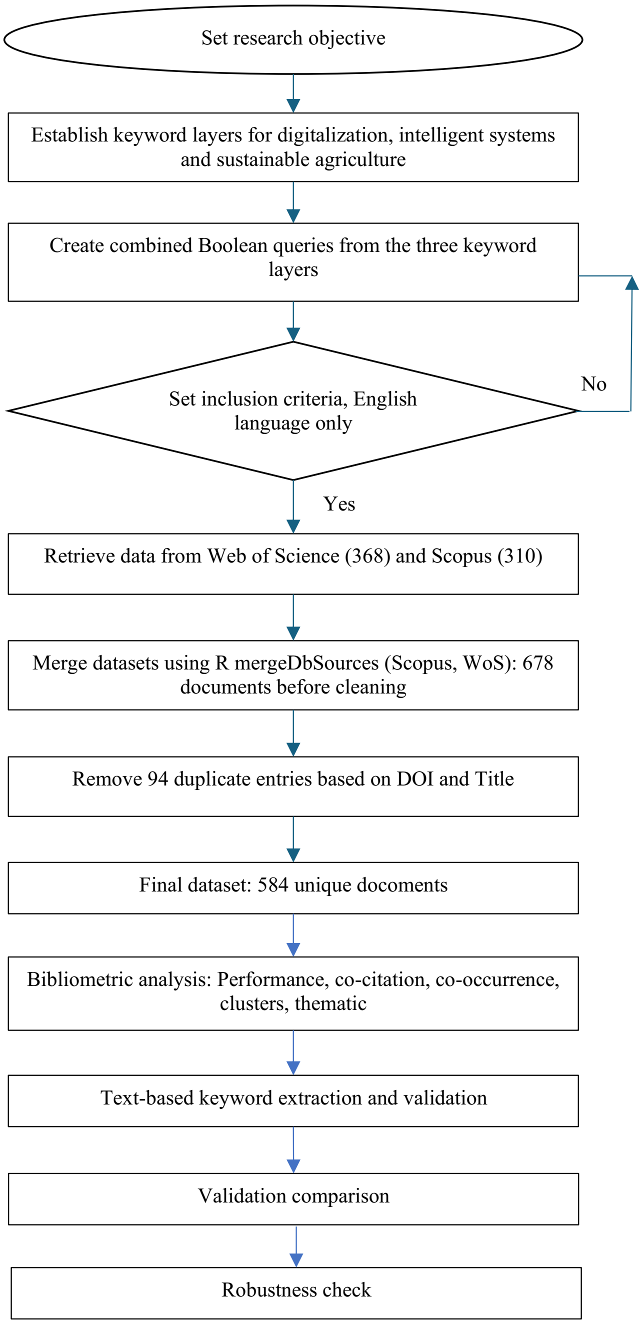
Cluster	Keywords	Occurrences	Total link strength
Cluster 2	Knowledge-based systems	5	32
Cluster 2	Machine design	5	26
Cluster 3	Sustainable development	73	365
Cluster 3	Industrial systems	47	219
Cluster 3	Sustainability	34	146
Cluster 3	Industrial research	27	174
Cluster 3	Digitalization	18	66
Cluster 3	Circular economy	15	68
Cluster 3	Digital twin	11	63
Cluster 3	Industrial economics	11	51
Cluster 3	Digital technologies	9	42
Cluster 3	Geographic information systems	8	28
Cluster 3	Supply chains	8	45
Cluster 3	Blockchain	7	48
Cluster 3	Planning	7	35
Cluster 3	Energy utilization	6	40
Cluster 3	Environmental technology	6	39
Cluster 3	Industry	6	23
Cluster 3	Manufacture	6	34
Cluster 3	Economics	5	14
Cluster 3	Ecosystems	5	21
Cluster 3	Environmental impact	5	34
Cluster 4	Sustainable development	73	365
Cluster 4	Industry 4.0	65	339
Cluster 4	Smart manufacturing	19	120
Cluster 4	Automation	15	103
Cluster 4	Life cycle	15	64
Cluster 4	Digital transformation	12	60
Cluster 4	Competition	11	57
Cluster 4	Industrial revolutions	8	51
Cluster 4	Economic and social effects	7	39
Cluster 4	Manufacturing industries	7	29
Cluster 4	Production system	6	39
Cluster 4	Digitization	5	22
Cluster 4	Digitization	5	22
Cluster 4	Efficiency	5	25
Cluster 4	Industrial IoT	5	20
Cluster 4	Investments	5	33
Cluster 5	Artificial intelligence	25	125
Cluster 5	Industry 5.0	16	80
Cluster 5	Machine learning	14	71
Cluster 5	Energy efficiency	12	63
Cluster 5	Predictive maintenance	12	56
Cluster 5	Digital twins	9	39
Cluster 5	Energy	8	38
Cluster 5	Industrial processes	8	39
Cluster 5	Machine learning	7	58
Cluster 5	Soft computing	6	31
Cluster 5	Sustainable manufacturing	6	32
Cluster 5	Energy conservation	5	20
Cluster 5	Green manufacturing	5	41

Table A6
Thematic analysis of research themes

Keywords	Dim1	Dim2
Industry 4.0	0.43	–0.37
Sustainability	0.83	–0.62
Sustainable development	–0.33	–1.00
Intelligent systems	–0.99	0.40
Internet of Things	–0.69	0.84
IoT	–0.32	0.43
Artificial intelligence	–0.30	–0.10
Management	1.45	–0.12
Industrial systems	–0.69	–0.83
Internet	0.70	2.51
Cyber-physical systems	–0.40	0.74
Digitalization	0.80	–0.92
Design	0.98	0.10
Smart manufacturing	0.95	–0.45
Circular economy	1.39	–1.57
Framework	2.05	0.61
Machine learning	–0.55	0.47
Industry 5.0	0.43	–0.02
Internet of Things (IoT)	–0.58	1.12
Mechanical engineering	–0.48	0.23
Embedded systems	–1.54	–0.50
Engineering education	–0.54	–0.92
Performance	1.34	–0.62
Systems	1.32	0.81
Information systems	–1.00	0.61
Model	1.07	0.82
Optimization	0.42	1.18
Automation	–0.62	–0.42
Big data	0.50	0.20
Manufacturing	1.64	0.13
Digital twin	–0.19	0.77
Energy	0.83	–1.01
Engineering systems	–0.69	–0.72
System	0.66	0.82
Things	0.71	3.27
Challenges	2.03	0.30
Industry	0.45	–0.14
Information management	–1.36	–0.48
Security	–0.26	1.29
Technology	–0.38	0.52
Digital transformation	0.75	–0.20
Industrial research	–0.81	–0.86
Innovation	1.67	–0.11
Life cycle	–0.81	–1.07
Future	1.72	0.84
Predictive maintenance	–0.39	–0.35
Technologies	2.57	–0.56
Decision-making	–1.11	0.01
Robotics	–0.92	0.00
Simulation	0.47	0.02
Sustainable manufacturing	0.98	–0.89

Appendix B

Workflow of the bibliometric analysis



Appendix C

Literature streams and study contribution

Research stream	Main focus	References	Main contribution	Remaining limitation
Digital agriculture	Digital transformation in farming systems	Bhardwaj et al., 2025	Explains digital tools in agriculture	Limited focus on mechanical systems
IoT and smart systems	Sensors, IoT, CPS, AI, digital twins	K. P. Singh et al., 2026; E. A. Lee, 2008	Shows smart connectivity and data functions	Weak link with sustainability outcomes
Industry 4.0 and Industry 5.0	Smart manufacturing and production systems	Atif, 2023; Trentesaux et al., 2016	Links digitalization with industrial models	Agricultural machinery is less explicit
Sustainability transitions	Energy efficiency, circularity, green production	Geels, 2002; Markard et al., 2012	Explains system-level sustainability change	Digital machinery applications remain scattered
Current study	Digitalization, smart systems, sustainability, agricultural machinery	Present study	Integrates three layers in one bibliometric design	Focuses on bibliometric evidence, not field testing