Technological Tools Based on Artificial Intelligence in the Sugar Industry: A Bibliometric Analysis and Future Perspectives for Energy Efficiency

Herramientas tecnológicas basadas en inteligencia artificial en la industria azucarera: un análisis bibliométrico y perspectivas de futuro para la eficiencia energética

Ferramentas Tecnológicas Baseadas em Inteligência Artificial na Indústria Açucareira: Uma Análise Bibliométrica e Perspectivas Futuras para Eficiência Energética

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Abstract

Introduction: The application of Artificial Intelligence –AI– in industrial sugar production, particularly in sensor data and systems management, is rapidly evolving towards real-time monitoring programs that offer valuable recommendations and decision-making support within the sugar industry. **Methodology:** This comprehensive bibliometric analysis of 125 Scopus-indexed articles highlights significant trends in the field, including surges in article production during 2017, 2018, 2021, and 2022, accounting for 34% of total publications. **Results:** Scientific production in this domain grew by 3.93% from 1969 to 2023. Most research (81%) originated from key countries, including Australia, Brazil, India, China, the Philippines, the United States, and France. Prominent journals played a pivotal role, representing 19% of publications. Noteworthy authors include Attard, Everingham, Meng, and Sexton, with four published articles each. Remarkably, 88% of researchers in this field are transitory. This study underscores dynamic growth in artificial intelligence applications in sugar production, emphasizing sustainability in data and systems management. **Conclusions:** The effective integration of these technologies holds the potential to enhance sustainability practices, optimizing efficiency and quality throughout the sugar production supply chain, thereby contributing to the attainment of Sustainable Development Goal 9. The utilization of artificial intelligence to optimize industrial sugar production represents technological innovation capable of improving the efficiency and infrastructure of the sugar industry, consequently fostering global sustainable development.

Keywords: Technological advancements; sugar industry; artificial intelligence

Resumen

Introducción: La aplicación de la Inteligencia Artificial –IA– en la producción industrial de azúcar, particularmente en la gestión de sistemas y datos de sensores, está evolucionando rápidamente hacia programas de monitoreo en tiempo real que ofrecen valiosas recomendaciones y apoyo a la toma de decisiones dentro de la industria azucarera. **Metodología**: Este análisis bibliométrico integral de 125 artículos indexados en Scopus destaca tendencias significativas en el campo, incluidos aumentos repentinos en la producción de artículos durante 2017, 2018, 2021 y 2022, que representan el 34% del total de publicaciones. **Resultados**: La producción científica en este ámbito creció un 3.93% entre 1969 y 2023. La mayor parte de la investigación (81%) se originó en países clave, incluidos Australia, Brasil, India, China, Filipinas, Estados Unidos y Francia. Las revistas destacadas desempeñaron un papel fundamental, representando el 19% de las publicaciones. Entre los autores destacables se encuentran Attard, Everingham, Meng y Sexton, con cuatro artículos publicados cada uno. Cabe destacar que el 88% de los investigadores en este campo son transitorios. Este estudio subraya el crecimiento dinámico de las aplicaciones de inteligencia artificial en la producción de azúcar, enfatizando la sostenibilidad en la gestión de datos y sistemas. **Conclusiones**: La integración efectiva de estas tecnologías puede mejorar las prácticas de sostenibilidad, optimizando la eficiencia y la calidad en toda la cadena de suministro de la producción de azúcar, contribuyendo al logro del Objetivo de Desarrollo Sostenible 9. Esto se debe a que el uso de inteligencia artificial para optimizar la producción industrial de azúcar representa una innovación tecnológica que puede mejorar la eficiencia y la infraestructura de la industria azucarera. Esto, a su vez, puede contribuir a lograr el desarrollo sostenible a escala global.

Palabras clave: Avances tecnológicos; industria azucarera; inteligencia artificial

Resumo

Introdução: A aplicação da Inteligência Artificial –IA– na produção industrial de açúcar, particularmente em dados de sensores e gestão de sistemas, está a evoluir rapidamente para programas de monitorização em tempo real que oferecem recomendações valiosas e apoio à tomada de decisões na indústria açucareira. **Metodologia:** Esta análise bibliométrica abrangente de 125 artigos indexados pela Scopus destaca tendências significativas na área, incluindo aumentos na produção de artigos durante 2017, 2018, 2021 e 2022, representando 34% do total de publicações. **Resultados:** A produção científica neste domínio cresceu 3,93% entre 1969 e 2023. A maior parte da investigação (81%) teve origem em países-chave, incluindo Austrália, Brasil, Índia, China, Filipinas, Estados Unidos e França. Periódicos proeminentes desempenharam um papel fundamental, representando 19% das publicações. Autores notáveis incluem Attard, Everingham, Meng e Sexton, com quatro artigos publicados cada. Notavelmente, 88% dos investigadores nesta área são transitórios. Este estudo ressalta o crescimento dinâmico das aplicações de inteligência artificial na produção de açúcar, enfatizando a sustentabilidade na gestão de dados e sistemas. **Conclusões:** A integração eficaz destas tecnologias pode melhorar as práticas de sustentabilidade, otimizando a eficiência e a qualidade em toda a cadeia de abastecimento da produção de açúcar, contribuindo para a concretização do Objetivo de Desenvolvimento Sustentável 9. Isto porque a utilização da inteligência artificial para otimizar a produção industrial de açúcar representa uma inovação tecnológica que pode melhorar a eficiência e a infraestrutura da indústria açucareira. Isto, por sua vez, pode contribuir para alcançar o desenvolvimento sustentável à escala global.

Palavras-chave: Avanços tecnológicos; indústria açucareira; inteligência artificial

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1. Introduction

The food industry is a crucial sector in the manufacturing industry, responsible for acquiring raw materials, whether of animal or vegetable origin, and converting them into products ready for consumption or use. Managing the supply chain in the food sector is a complex challenge, given the perishable nature of products, unpredictable supply fluctuations, and stringent requirements for food safety and sustainability (Iturralde et al., 2021; Verdouw et al., 2016).

Innovations in the food industry have paved the way for new technical methods of food production and processing. To meet the growing market demand and achieve efficient production, the food industry is constantly seeking new processing and control techniques. The use of smart devices has played a pivotal role in integrating information between suppliers and manufacturers, enabling a more agile response to market demands and the creation of new ways to interact with end consumers. Consequently, this leads to a sustainable competitive advantage within the supply chain (Kakani et al., 2020).

According to Koulourius et al. (2021), technologies based on computing, software, networks, and sensors are not recent discoveries. However, the exponential growth of these technologies has brought about a significant disruption in established patterns, leading to paradigm shifts in business, society, and individual behavior. This systemic impact extends across national boundaries, affecting both organizations and society, both at the national and international levels.

Given the relevance of this topic, an additional review of the global scientific literature was carried out, with a focus on articles published in journals that concentrate on various AI methods applied to agroindustry. Some of the highlighted studies include Rooh et al. (2015), which provide a detailed analysis of the integration of Artificial Intelligence –AI– with classical approaches and offer guidance for researchers in the agricultural field to explore new study variables. Dongre and Gandhi (2016) analyze information learned through repeated experiences, emulating the human learning process, to provide classification, pattern recognition, optimization, and future predictions in the livestock sector. Evans et al. (2017) address the implications of farmers' decision-making styles in the context of AI adoption, as well as crop management through technological platforms. Patrício and Rieder (2018) examine the applicability of AI in disease detection, grain quality assessment, and phenotyping in grain production. Eli-Chukwu (2019) conducts a comprehensive review of AI applications to increase agricultural productivity, with a focus on soil management, crop cultivation, weed control, and disease management. Chia et al. (2020) show a mapping of the relationships between climatic parameters and evapotranspiration to provide real-time data for water resource management and irrigation management.

A comprehensive review of the global scientific literature was conducted, focusing on the analysis of articles published in journals that address a wide range of AI methods applied to the sugar industry.

2. Materials and methods

This study has been designed to examine the intellectual production related to the use of technology-based artificial intelligence tools in the sugar industry, with a focus on sustainability. To achieve this objective, we have defined the following variables and their descriptors (Table 1).

Table 1. Standardization of keywords.

Variable	Descriptors
Technology-based artificial intelligence tools	"automation" "predictive systems" "artificial intelligence"
Sugar industry	"sugar cane" "panela"

Source: Authors.

Based on the identification of these descriptors, we have formulated the following search equation in the Scopus database: (TITLE-ABS-KEY ("automation") OR TITLE-ABS-KEY ("predictive systems" OR TITLE-ABS-KEY ("artificial intelligence")) AND TITLE-ABS-KEY ("sugar cane" OR TITLE-ABS-KEY ("panela")). Subsequently, we analyzed the data obtained from Scopus using the R Studio software with its Bibliometrix package and VOSviewer software, aiming to identify trends and contributions in the field of sustainability in the sugar industry.

3. Results and discussions

Table 2 allows us to identify the overarching elements associated with scientific production in the knowledge area, revealing a recent growth of 3.93%. This growth is observed across a total of 84 sources, involving 442 authors who contributed to these publications.

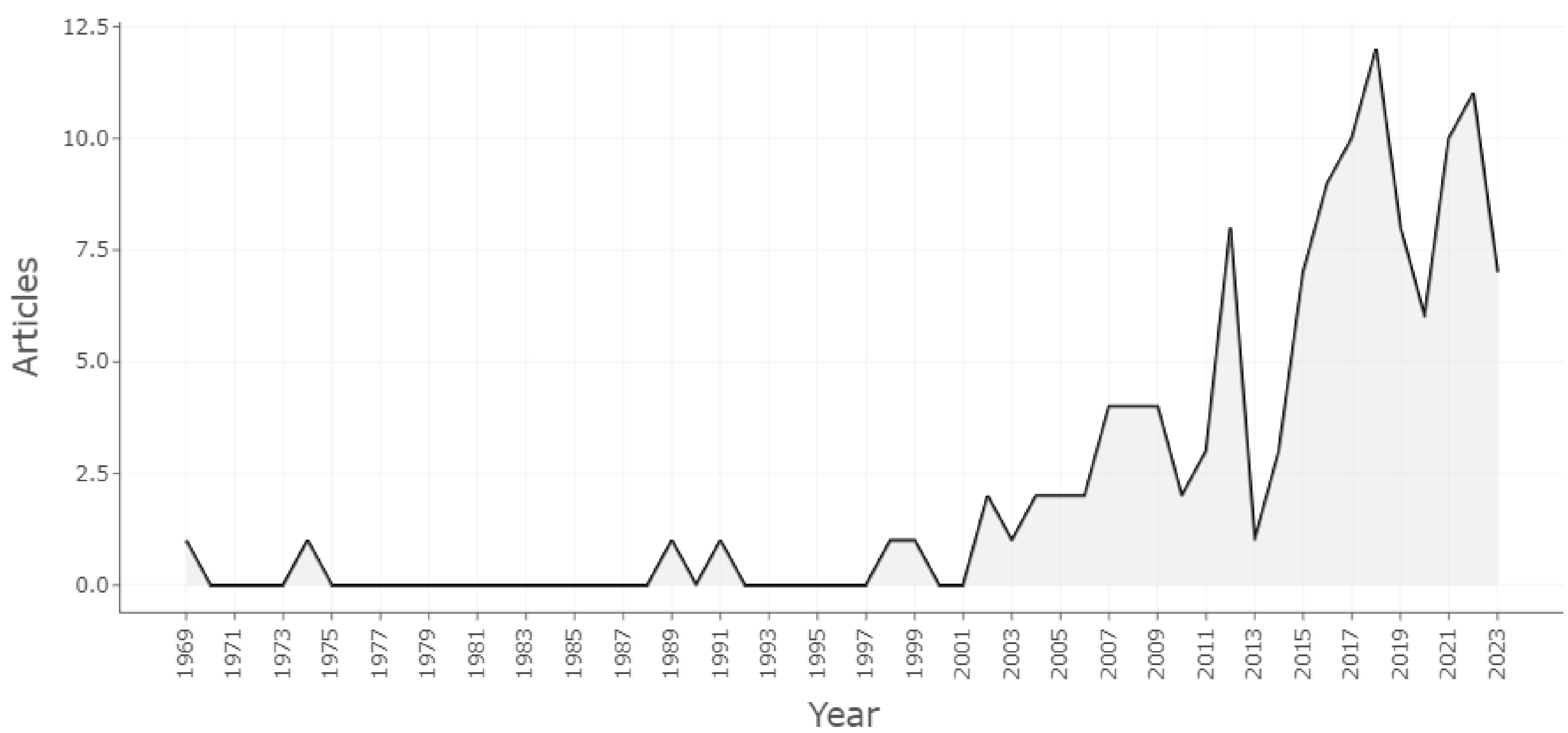
Table 2. General search information.

Main Information About Data	
Timespan	1969-2023
Sources (Journals, Books, etc.)	84
Documents	125
Annual Growth Rate %	3.93
Document Average Age	8.6
Average citations per doc	14.6
References	3214
Document Contents	
Keywords Plus (ID)	1658
Author's Keywords (DE)	412
Authors	
Authors	442
Authors of single-authored docs	14
Authors Collaboration	
Single-authored docs	14
Co-Authors per Doc	4.05
International co-authorships %	17.6
Document Types	
Article	70
Book chapter	2
Conference paper	49
Conference review	1
Review	2
Short survey	1

Source: Authors.

Moreover, the upward trajectory of scientific production becomes even clearer when examining Figure 1. Notably, the years 2017 (10), 2018 (12), 2021 (10), and 2022 (11) stand out, reflecting a significant surge in publications related to the research topic. These years collectively account for 34% of all research conducted in this area.

Figure 1. Annual scientific production based on information from Scopus.



Source: Authors.

The most relevant sources are based on publication frequency in the field, employing percentiles as outlined by Bradford's Law. Bradford's Law categorizes journals into three performance zones, each with a corresponding increase in the number of journals and a similar proportion of articles. We applied Bradford's Law to ascertain its value (Martín-del-Río et al., 2021).

Table 3 displays the percentages associated with each Bradford Law Zone. It is noteworthy that Zone 1 contains the highest number of publications at 34% (43).

Table 3. Bradford's Law.

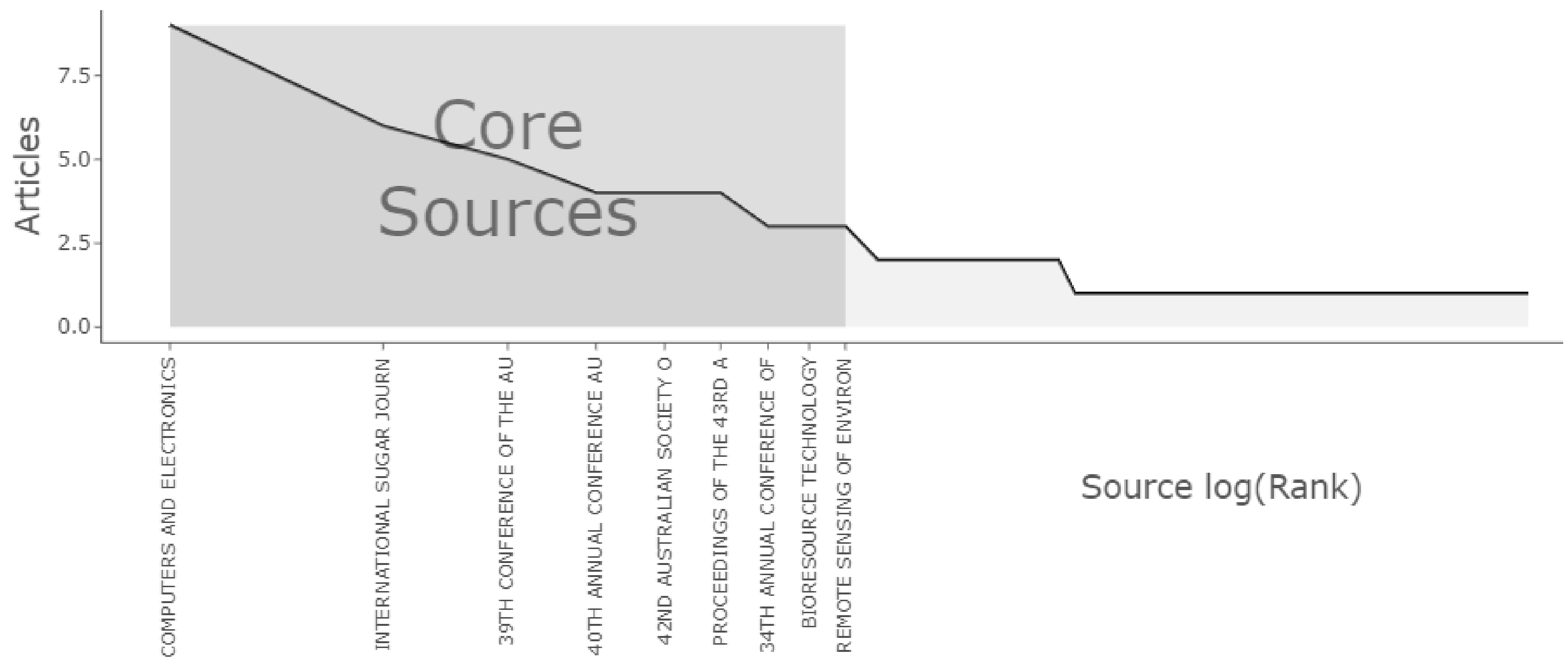
Zone	No. of Journals	No. of Titles	(%)
Zone 1	10	43	34.40
Zone 2	33	41	32.80
Zone 3	41	41	32.80

Source: Authors.

In a similar vein, Figure 2 showcases the most influential journals by this law (Martín-del-Rio et al., 2021).

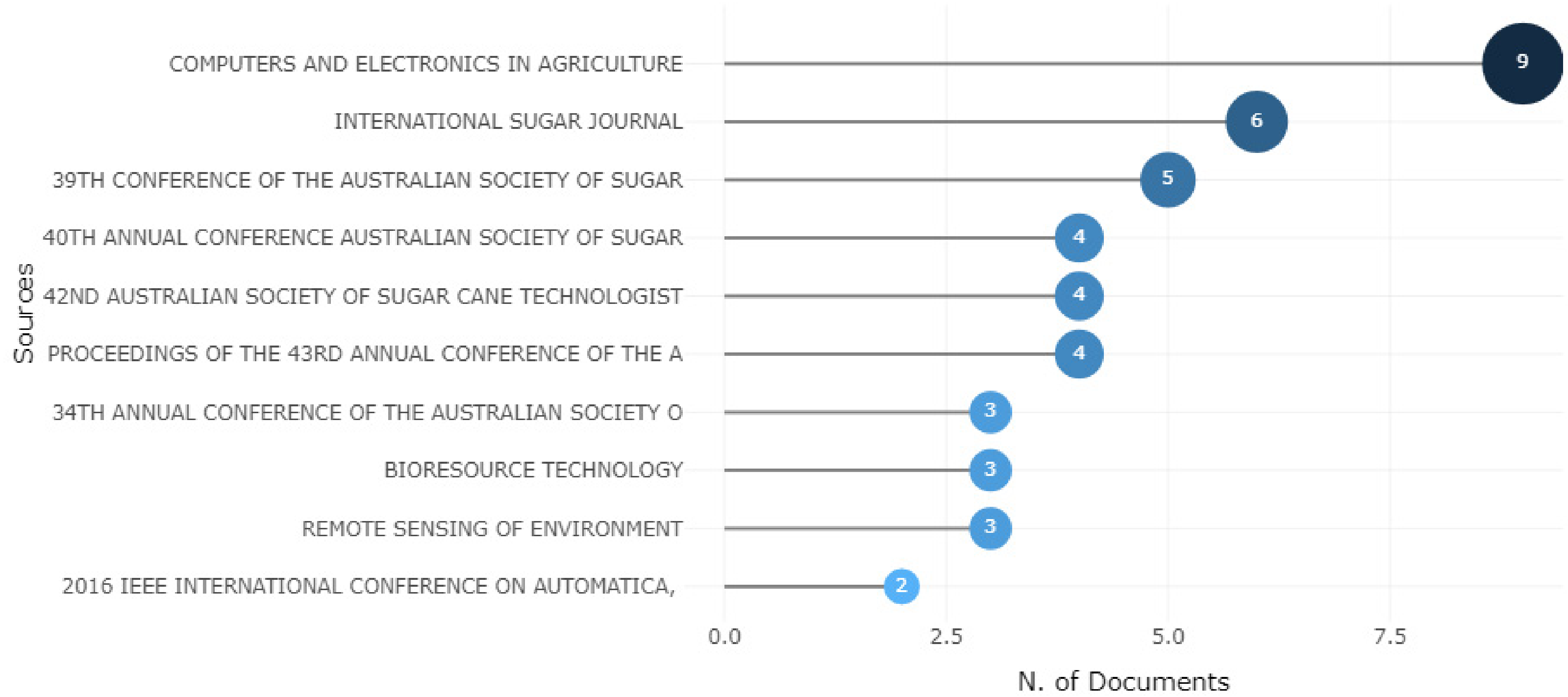
Consistent with the above, in Figure 3, we observe that Computer and Electronics in Agriculture leads the field with nine publications, followed by the International Sugar Journal with six, and the 39th Conference of the Australian Society of Sugar with five contributions.

Figure 2. Bradford's Law is based on information from Scopus.



Source: Authors.

Figure 3. Most Relevant Sources use R software based on Scopus data.



Source: Authors.

The journal "Computer and Electronics in Agriculture" features publications that delve into the use of artificial intelligence for developing predictive models for sugarcane production and yield, as well as the application of precision agriculture strategies (Maldaner et al., 2021). It also includes research on the performance classification of sugarcane (Natarajan et al., 2016). Another related study examines the development of a decision support system capable of providing digital assistance to those responsible for planning sugarcane harvesting tasks (Stray et al., 2012).

The most cited article in the International Sugar Journal explores trends in the automation of sugarcane production. It highlights advances in cane transportation equipment, improvements in harvester management practices, and research into sugarcane bagasse management (Ridge, 2003).

In terms of countries, Australia emerges as the leading contributor to scientific productivity with 123 contributions, followed by Brazil with 99, India with 59, China with 54, the Philippines with 22, the USA with 21, and France with 15, among others. It is worth noting that collaborative research efforts involving researchers from different countries are prevalent, with notable co-authorship between Australia and Brazil. This collaboration is further illustrated in Table 4.

Table 4. Scientific Production by Country.

Country	Frequency
Australia	123
Brazil	99
India	68
China	54
Philippines	22
USA	21
France	15
Germany	11
Thailand	10
UK	10
Total	433

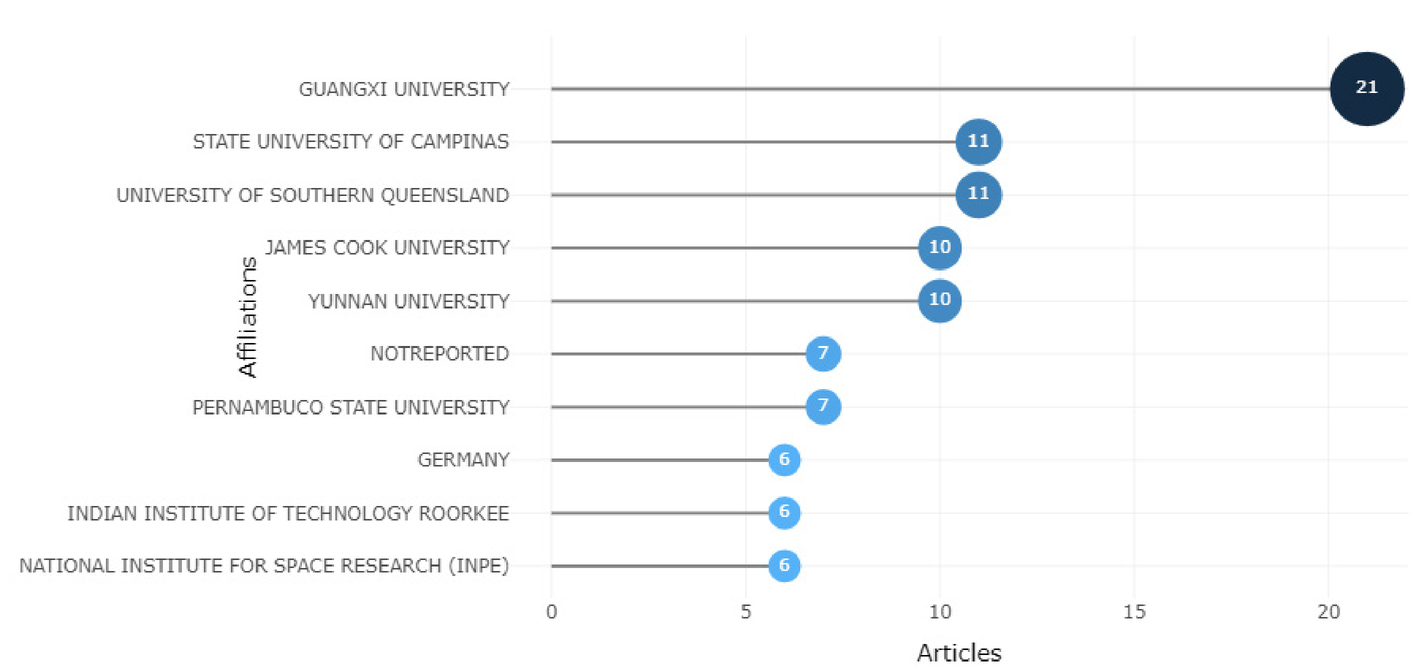
Source: Authors,

Australian publications account for 25% of the total contributions. Some of their research is focused on the automation of agricultural work, utilizing new detection and automation techniques with an emphasis on improving productivity in the sugarcane industry (Brett et al., 2019; West, 2021).

Other studies from Australia delve into the use of neural networks to create a deep-learning framework for monitoring sugar crystallization (Zhang et al., 2020). Additionally, they propose the development of a closed-loop irrigation system for sugarcane plantations using the Internet of Things, providing data on various variables for informed irrigation decision-making (Wang et al., 2020).

On the other hand, one of the most cited articles from Brazil explores the use of neural networks for the hydrolysis of sugarcane bagasse to produce bioethanol (Rivera et al., 2010).

Figure 4. Most relevant affiliations are based on Scopus data.

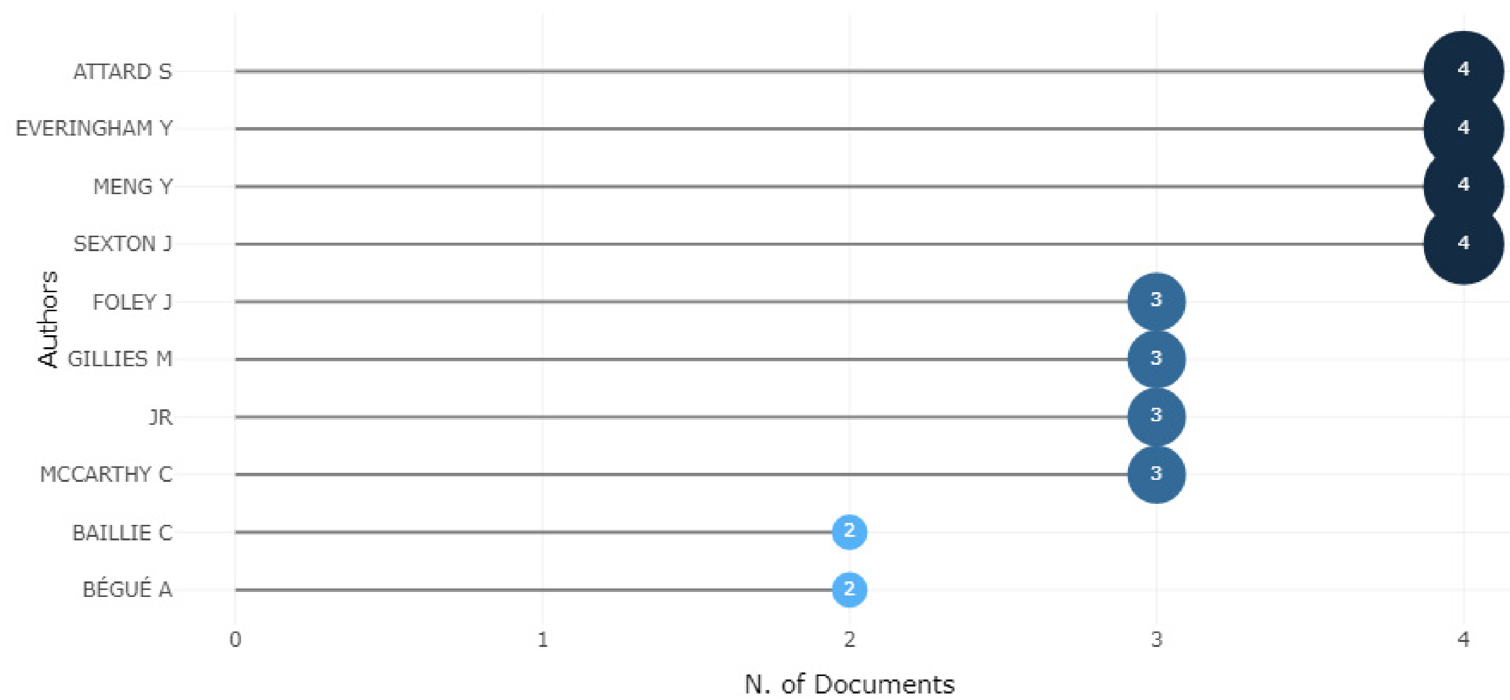


Source: Authors.

In line with these thoughts, Figure 4 illustrates the institutions that have made the most significant contributions to the study topic: Guangxi University (21), the University of Southern Queensland (11), and James Cook University (11). Together, they contribute to 13% of all publications, considering collaborative works among them.

To gauge individual researcher productivity, we reference the frequency index. Figure 5 reveals that Attard, Everingham, Meng, and Sexton lead with four publications each.

Figure 5. Most relevant authors use R software based on information from Scopus (2023).



Source: Authors.

Furthermore, Lotka's law (Table 5), allows us to map the production curve against the number of authors, providing a clearer understanding of author contributions to the field (Andreo-Martínez et al., 2020; Barrera et al., 2021). 88.3% of the authors have made only one contribution, followed by 9.9% who have made at least two, and the remaining 1.8% is evenly divided between those who have contributed three or four times. From this, it can be inferred that most authors researching this topic are transient contributors.

Table 5. Lotka's Law.

Documents written	N. of Authors	Proportion of Authors
1	391	0.883
2	44	0.099
3	4	0.009
4	4	0.009

Source: Author using R software (2023) based on information from Scopus.

Regarding the works of authors who have made the most contributions to the study topic, it's noteworthy that they have collaborative works related to improving irrigation systems and intelligent management using the internet (Gillies et al., 2017; Wang et al., 2018; Wang et al., 2020).

Table 6 presents the top twenty articles related to the study topic with the most citations. The three most prominent ones are Vieira et al. (2012), Kaab et al. (2019), and Badshah et al. (2012). Additionally, Table 7 provides a description of the ten most cited articles on the research topic.

Table 6. Most cited articles.

Articles	DOI	Total Citations
Object-Based Image Analysis and Data Mining were applied to a remotely sensed Landsat time series to map sugarcane over large areas (Vieira et al., 2012).	10.1016/j.rse.2012.04.011	205
Combined life cycle assessment and artificial intelligence for prediction of output energy and environmental impacts of sugarcane production (Kaab et al., 2019).	10.1016/j.scitotenv.2019.02.004	160
Use of an Automatic Methane Potential Test System for evaluating the biomethane potential of sugarcane bagasse after different treatments (Badshah et al., 2012).	10.1016/j.biortech.2012.02.022	117
Improving the efficacy of the Cr (VI) adsorption process on sustainable adsorbent derived from waste biomass (sugarcane bagasse) with the help of ant colony optimization (Karri et al., 2020).	10.1016/j.indcrop.2019.111927	103
Outlook for ethanol production costs in Brazil up to 2030, for different biomass crops and industrial technologies (Jonker et al., 2015).	10.1016/j.apenergy.2015.01.090	90
Integrating SPOT-5 time series, crop growth modeling, and expert knowledge for monitoring agricultural practices — The case of sugarcane harvest on Reunion Island (El Hajj et al., 2009).	10.1016/j.rse.2009.04.009	84
The effect of tuning, feature engineering, and feature selection in data mining applied to rainfed sugarcane yield modeling (Bocca & Rodrigues, 2016).	10.1016/j.compag.2016.08.015	70
Chapter 3 - Bioprocesses for Enzyme Production Using Agro-Industrial Wastes: Technical Challenges and Commercialization Potential (Kapoor et al., 2016).	10.1016/B978-0-12-802392-1.00003-4	67
Fast chromatographic determination of polycyclic aromatic hydrocarbons in aerosol samples from sugar cane burning (Godoi et al., 2004).	10.1016/j.chroma.2003.10.048	66
Artificial intelligence-based modeling and optimization of poly(3-hydroxybutyrate-co-3-hydroxyvalerate) production process by using Azohydromonas lata MTCC 2311 from cane molasses supplemented with volatile fatty acids: A genetic algorithm paradigm (Zafar et al., 2012).	10.1016/j.biortech.2011.10.024	54
Enzymatic hydrolysis of sugarcane bagasse for bioethanol production: determining optimal enzyme loading using neural networks (Rivera et al., 2010).	10.1002/jctb.2391	54
Mapping skips in sugarcane fields using object-based analysis of unmanned aerial vehicle (UAV) images (De Souza et al., 2017).	10.1016/j.compag.2017.10.006	53
An optimization-based seasonal sugarcane harvest scheduling decision support system for commercial growers in South Africa (Stray et al., 2012).	10.1016/j.compag.2012.01.009	47
Hybrid learning of fuzzy cognitive maps for sugarcane yield classification (Natarajan et al., 2016).	10.1016/j.compag.2016.05.016	46
Production of biomass-degrading multienzyme complexes under solid-state fermentation of soybean meal using a bioreactor (Vitcosque et al., 2012).	10.1155/2012/248983	36
A simple and practical control of the authenticity of organic sugarcane samples based on the use of machine-learning algorithms and trace elements determination by inductively coupled plasma mass spectrometry (Barbosa et al., 2015).	10.1016/j.foodchem.2015.02.146	35
A multiplex set of species-specific primers for rapid identification of members of the genus Saccharomyces (Muir et al., 2011).	10.1111/j.1567-1364.2011.00745.x	35
Production of potentially hazardous respirable silica airborne particulate from the burning of sugarcane (Le Blond et al., 2008).	10.1016/j.atmosenv.2008.03.018	33
Generalized space-time classifiers for monitoring sugarcane areas in Brazil (Luciano et al., 2018).	10.1016/j.rse.2018.06.017	31
Development of adaptive modeling techniques to describe the temperature-dependent kinetics of biotechnological processes (Rivera et al., 2007).	10.1016/j.bej.2007.02.011	31

Source: Authors.

Table 7 presents the key research areas in the field of sugar cane and its applications in the industry, emphasizing automation, sustainability, and process optimization.

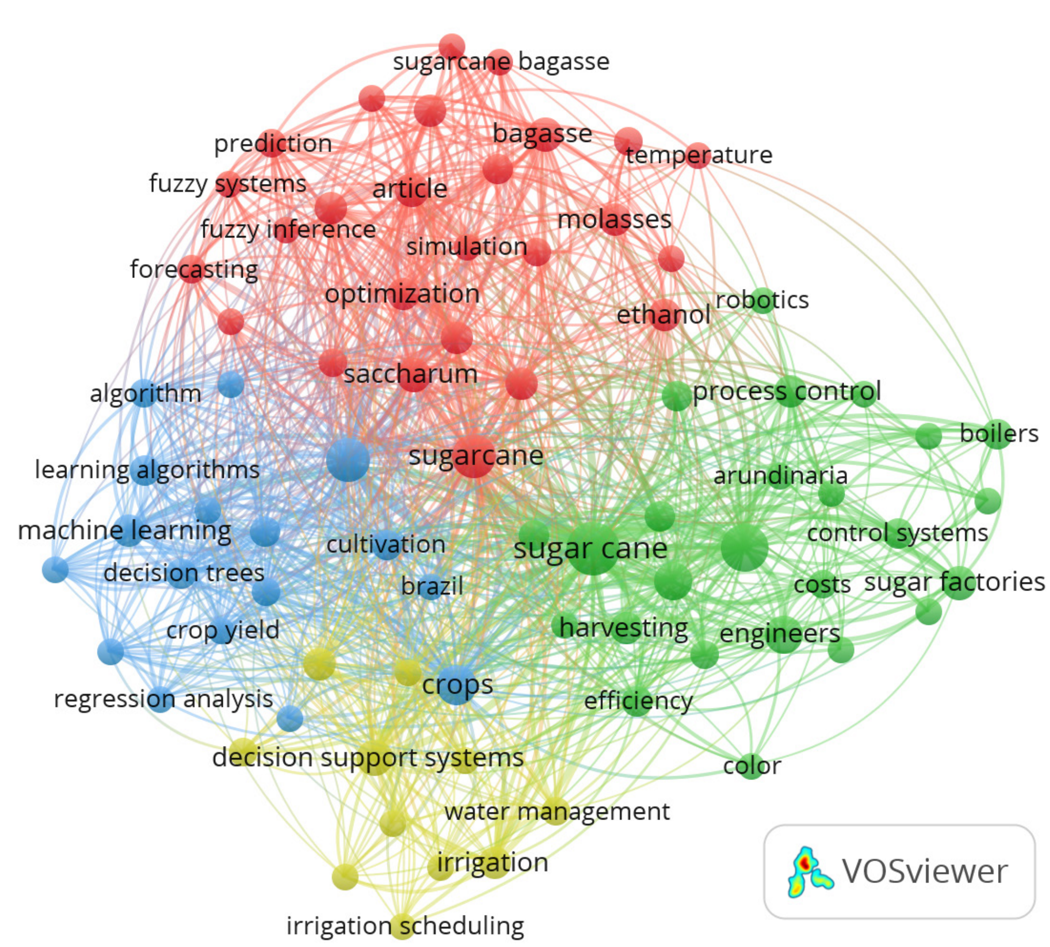
TABLE 7. TEN MOST CITED ARTICLES.

Highlight	Source	Citation
Development of a methodology for the extensive mapping automation of sugar cane plantations using Object-Based Image Analysis and Data Mining.	Remote Sens Environ	Vieira et al. (2012).
Use of artificial intelligence and neural networks to predict the energy and environmental impact of sugar cane production.	Sci Total Environ	Kaab et al. (2019).
Analysis of the biogas potential of sugar cane bagasse through a multi-channel analysis.	Bioresour Technol	Badshah et al. (2012).
Utilization of agricultural biomass waste, specifically sugar cane bagasse, as chromium absorbents in water.	Ind Crops Prod	Karri et al. (2020).
Economic perspective study of the ethanol industry in Brazil, considering the use of different raw materials and industrial processes, including biomass.	Appl Energy	Jonker et al. (2015).
Modeling the growth of sugar cane crops through the analysis of satellite image time series.	Remote Sens Environ	El Hajj et al. (2009).
Modeling sugar cane yield using information provided by agricultural mechanisms and data mining.	Comput Electron Agric	Bocca & Rodrigues (2016).
Bioprocesses are used to manufacture enzymes from agro-industrial residues, addressing technical challenges and commercial viability.	Agro-Ind Wastes As Feedstock For Enzym Prod	Kapoor et al. (2016).
Determination of the presence of polycyclic aromatic hydrocarbons in aerosols derived from sugar cane burning.	J Chromatogr A	Godoi et al. (2004).
Modeling and process improvement of sugar cane molasses using artificial intelligence.	Bioresour Technol	Zafar et al. (2012).

Source: Authors.

The cluster analysis using VOSviewer, as shown in Figure 6, reveals the terms with the highest impact grouped by co-occurrence. It is evident that keywords such as "sugarcane," "artificial intelligence," "automation," "crops," and "*Saccharum*" stand out.

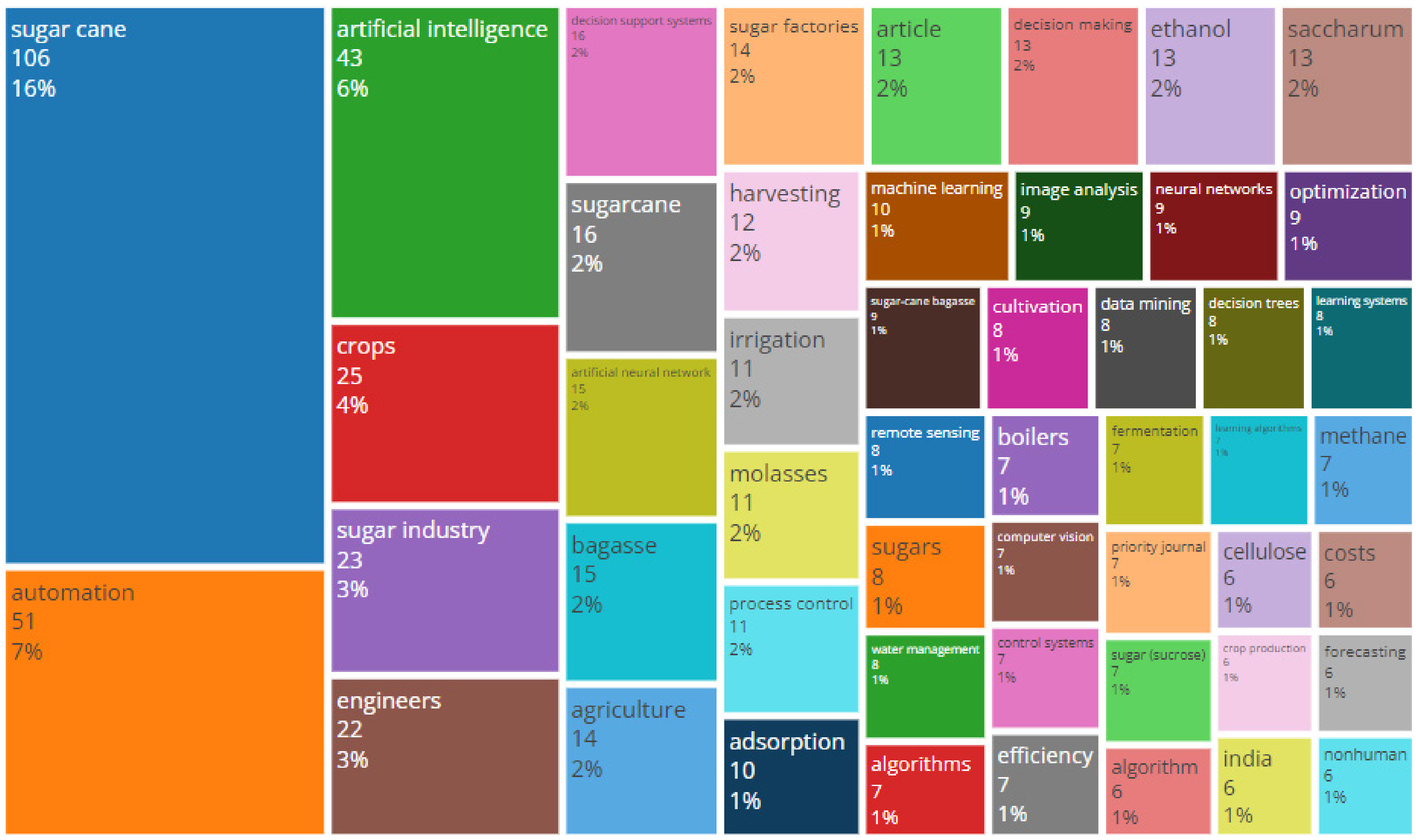
Figure 6. Co-occurrence of keywords, source: author using VOSviewer software based on Scopus data.



Source: Authors (VOSviewer, 2019).

Several of the key terms associated with the field of artificial intelligence-based tools for the development of the sugar industry can be observed in Figure 7.

Figure 7. Keywords, source: author using R software based on information from Scopus.



Source: Authors.

The future perspectives of technological tools based on artificial intelligence in the sugar industry are promising and cover several areas of development and innovation. One possible future direction is precision agriculture where AI-based tools can further improve precision agriculture in the sugar industry. Machine learning algorithms can be used to analyze data from sensors, drones, and satellites to optimize planting, irrigation, and harvesting practices. This can lead to higher yields and resource efficiency (Shaikh et al., 2022).

Artificial intelligence can be used to develop advanced disease detection systems. Machine vision and image recognition algorithms can identify signs of disease or pests in sugarcane plantations early on, enabling timely intervention and reducing crop loss (Jha et al., 2019).

Future developments could focus on reducing the environmental impact of sugarcane production. AI can help optimize irrigation schedules, reduce the use of chemical pesticides, and minimize water waste, leading to more sustainable practices (Talaviya et al., 2020).

AI can be used to improve the energy efficiency of sugar mills and refineries. Predictive maintenance models can help prevent equipment breakdowns, while AI-based process optimization can reduce energy consumption and improve overall efficiency (Gozá et al., 2002).

Advanced AI tools can be integrated into supply chain management systems. This can help in real-time tracking of sugarcane from the farm to the refinery, ensuring quality control and minimizing waste (Goswami et al., 2022).

AI-based predictive analytics can help predict sugar prices, demand fluctuations, and market trends. This can allow sugar producers to make informed decisions about production levels and pricing strategies (Kantasa-Ard et al., 2019).

Research can focus on finding innovative ways to utilize waste from sugarcane processing. AI can help identify valuable byproducts and develop processes to convert them into marketable products, reducing waste and increasing profitability (Solarte-Toro & Cardona, 2023).

AI can play a role in sugarcane genetic improvement programs. By analyzing genetic data, AI can help breeders select the most promising varieties for specific conditions, potentially leading to higher yields and disease resistance (Yoosefzadeh-Najafabadi et al., 2023).

As the sugar industry faces increasing scrutiny regarding environmental and sustainability regulations, AI can help monitor and ensure compliance with these standards (Stuurman & Lachaud, 2022).

The future of technological tools based on artificial intelligence in the sugar industry presents great potential to improve efficiency, sustainability, and global productivity. Ongoing research, innovation, and collaboration are key to unlocking these benefits and addressing the challenges facing the industry.

4. Conclusions

Based on the analysis of 125 articles in this bibliometric study, using information obtained from Scopus on Artificial Intelligence-based tools in the sugar industry, the following observations can be made:

The highest peaks in publications occurred in the years 2017, 2018, 2021, and 2022, accounting for 34% of the total published works. The scientific production analyzed from 1969 to 2023 shows a growth rate of 3.93%.

Approximately 81% of all publications are concentrated in Australia, Brazil, India, China, the Philippines, the United States, and France. Furthermore, the journals with the highest publication output on this topic are Computer and Electronics in Agriculture, International Sugar Journal, 39th Conference of the Australian Society of Sugar, and 40th Annual Conference Australian Society of Sugar Cane Technologists (ASSCT) 2018. These journals account for 19% of all publications, while the rest of the publications are distributed across various other journals.

Authors with the most published articles include Attard, Everingham, Meng, and Sexton, each contributing four articles. It is worth noting that 88% of researchers in this field are transient. The keywords most associated with the research topic are sugar cane, artificial intelligence, automation, crops, and *Saccharum*.

This research underscores the relevance of the use of artificial intelligence-based tools in the sugar industry and highlights the need for sustainable practices in this sector to address current and future challenges.

Conflict of Interest

The authors declare that they have no conflict of interest.

Author contributions

Hugo Hernández Palma: Original draft preparation, Methodology, Data curation.
Jonny Rafael Plaza Alvarado: Methodology, and Investigation.
Jesús Enrique García Guiliany: Conceptualization, Visualization, Formal Analysis and Writing Reviewing.
Andrea Liliana Moreno Ríos: Writing and review & editing.

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