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Systematic Review

# Leveraging Machine Learning for Advancing Circular Supply Chains: A Systematic Literature Review

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**Abstract:** *Background*: Circular supply chains (CSCs) aim to minimize waste, extend product lifecycles, and optimize resource efficiency, aligning with the growing demand for sustainable practices. Machine learning (ML) can potentially enhance CSCs by improving resource management, optimizing processes, and addressing complexities inherent in CSCs. ML can be a powerful tool to support CSC operations by offering data-driven insights and enhancing decision-making capabilities. *Methods*: This paper conducts a systematic literature review, analyzing 66 relevant studies to examine the role of ML across various stages of CSCs, from supply and manufacturing to waste management. *Results*: The findings reveal that ML contributes significantly to CSC performance, improving supplier selection, operational optimization, and waste reduction. ML-driven approaches in manufacturing, consumer behavior forecasting, logistics, and waste management enable companies to optimize resources and minimize waste. Integrating ML with emerging technologies such as IoT, blockchain, and computer vision further enhances CSC operations, fostering transparency and automation. *Conclusions*: ML applications in CSCs align with broader sustainability goals, contributing to environmental, social, and economic sustainability. The review identifies opportunities for future research, such as the development of real-world case studies further to enhance the effects of ML on CSC efficiency.

**Keywords:** circular supply chain; circular economy; machine learning; artificial intelligence; systematic literature review

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## 1. Introduction

Due to environmental and resource issues, CSCs are drawing more interest from scholars and practitioners. CSCs generate value by extending the life cycles of products, components, and materials through coordinated forward and reverse SCs [1] (p. 709). The primary objectives of CSCs are to close resource loops through recycling or remanufacturing, increase resource efficiency by using fewer resources throughout the product life-cycle, and extend product lifetimes through design changes or repairs. Furthermore, CSC encompasses reverse logistics and closed-loop SCs (CLSCs) [1]. However, CSCs are conceptually different from CLSCs [2]. CLSCs involve returning used products to the same producer within the same SC for recycling, reuse, or remanufacturing. In contrast, CSCs consider more broadly the return of materials to the original SC sector (closed-loop), other sections of the same SC (open-loop), or even to other SCs (open-loop).

In addition to these distinctions, we clarify that by sustainability in this study, we are primarily referring to environmental sustainability, which focuses on minimizing environmental impacts by reducing resource use and waste generation throughout the SC. By circularity, we mean the goals of CSCs, which include closing resource loops through recycling or remanufacturing, increasing resource efficiency by utilizing fewer resources across the product life cycle and extending product lifetimes through design modifications or repairs. CSCs generate value by extending the life cycles of products, components, and materials through coordinated forward and reverse SCs, contributing significantly to the broader environmental sustainability goals.

To move forward to CSCs, significant modifications are needed across all stages of SCs [3]. One type of such modification is the introduction of ML algorithms to SCs facilitating the transition to circularity [4,5]. For instance, Kazancoglu et al. [6] determine ML and data mining as the most efficient big data solutions for circularity transition in dairy SC. Moreover, in recent years, there has been growing interest in applying ML techniques in the context of circular economy (CE) and sustainable SCs. Several literature reviews have focused on the potential of ML and artificial intelligence (AI) to enhance sustainability and circularity in various industries, including construction, transportation, healthcare, and manufacturing. These reviews have established the importance of digitalization in CE research [4,5,7–14]. Still, they do not specifically explore the use of ML technology and their algorithms in SCs for advancing circularity strategies.

To address this research gap, our study takes a unique perspective by focusing specifically on the application of ML techniques in different stages of CE-based SCs. To structure our analysis, we adopt a comprehensive framework that covers the entire SC, from sourcing to waste management. Our objective is to perform a content analysis of existing literature using this framework and develop some research propositions to identify specific areas where ML can be applied throughout the CSC to implement circularity strategies in SCs effectively.

ML is defined as "a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data or to make other types of decisions under uncertainty" [15]. Figure 1 [15] provides a classification of the main areas and algorithms of ML.

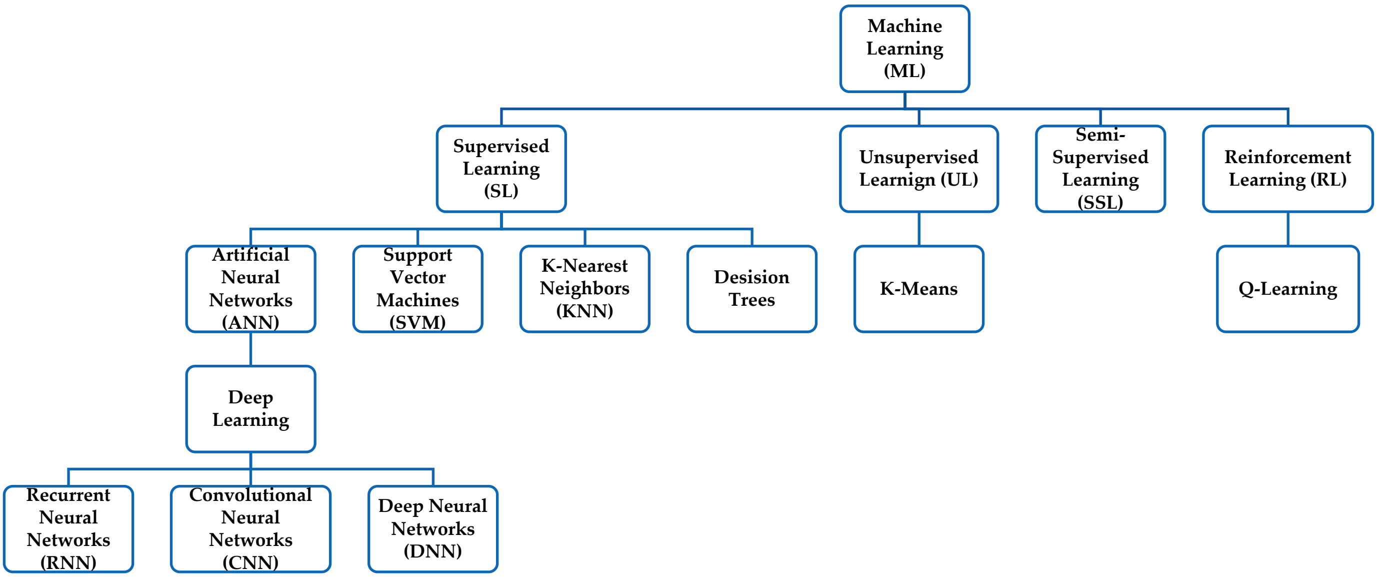


**Figure 1.** Learning types and main algorithms in ML.

Supervised learning uses labeled data to make predictions. In this type of learning, the model is trained on a dataset that includes input-output pairs, allowing it to learn the mapping function between the inputs and the expected outputs. Supervised learning algorithms, such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Decision Trees, and K-Nearest Neighbors (KNN), are highly effective for tasks like classification and regression. These algorithms are widely used in industries with large quantities of labeled data, such as manufacturing and SC management, enabling optimization and predictive maintenance. In contrast, unsupervised learning finds patterns in unlabeled data, meaning the model must independently discover the structure in the dataset without any predefined output labels. Algorithms like K-Means clustering are typical in unsupervised learning. These algorithms are beneficial in scenarios like market segmentation, anomaly detection, and exploring complex datasets where relationships between variables are not well understood. By identifying hidden patterns, unsupervised learning can support decision-making processes that were previously driven by human intuition.

Semi-supervised learning combines labeled and unlabeled data, which is especially useful when obtaining labeled data is expensive or time-consuming. This learning type leverages the small set of labeled data to understand better the structure of the larger set of unlabeled data. Semi-supervised learning algorithms are highly applicable in domains like fraud detection and medical diagnostics, where annotated data are scarce, but leveraging unlabeled data can lead to significant performance improvements.

Reinforcement learning (RL) is a different approach altogether. It trains a model through trial and error, where the model receives rewards or penalties based on its actions within an environment. One popular reinforcement learning algorithm is Q-Learning [16]. RL is widely used in industries requiring automation in dynamic environments, such as robotics, autonomous vehicles, and SC management. Additionally, deep learning, a subset of ML, focuses on using multi-layered neural networks, known as Deep Neural Networks (DNNs). Deep learning is especially effective in handling complex datasets like images, audio, and text, where traditional ML algorithms may struggle. Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) are two primary types of deep learning models. RNNs are particularly useful in sequence prediction tasks, such as time-series forecasting and language processing, while CNNs excel in image recognition and classification task technologies. By combining technologies, ML and deep learning enable companies to develop AI systems with human-like cognitive skills, like image recognition and decision-making [17].

By providing a detailed analysis of ML techniques in the context of CSCs and developing some research propositions, our study contributes to the existing literature by offering insights into the potential of ML to improve circularity in SCs. We intend to answer the research question: "*How does ML technology improve the performance of SCs toward circularity?*" Through synthesizing the current state of the art in the application of ML in CSCs, we develop research propositions, identify future research paths, detect CSCs and industries applying ML techniques, and determine executable ML methods for different sections of several CSCs and industries.

The following sections of this article are structured as follows: Section 2 details the methodology utilized in this systematic literature review, including adherence to the PRISMA guidelines (Preferred Reporting Items for Systematic Review and Meta-Analysis Protocol) and the systematic process of selecting and analyzing relevant studies. Section 3 analyses the content of the application of ML in the context of CSCs and summarizes the key findings and insights drawn from the systematic analysis of the literature. Finally, Section 4 explores the implications of these findings for both theory and practice, providing recommendations for future research and practical applications in enhancing SC circularity through ML technologies.

## 2. Materials and Methods

### *2.1. Search Strategy*

We employed a systematic literature review process to ensure a transparent, scientific, and replicable approach [18]. Our search was conducted in mid-2022 using the Scopus database, known for its strict criteria in indexing reliable academic research [19]. To provide a more comprehensive overview and reduce the risk of omitting relevant studies, we expanded our search to include the Web of Science (WOS) database. Both databases are renowned for their robust repositories of peer-reviewed literature across multiple disciplines, ensuring a high-quality selection of articles.

Our search strategy was meticulously designed to capture the intersection of ML and CSCs. We employed a set of targeted keywords, including "machine learning", "artificial intelligence", "circular supply chain", "circular economy", "closed-loop supply chain", "circularity", "reverse supply chain", and "reverse logistics". These terms were combined with Boolean operators (AND/OR) to ensure that all relevant studies were identified. The search was applied to the articles' titles, abstracts, and keywords sections. We limited the search to specific document types, including "Articles", "Articles in press", and "Review articles", all published in peer-reviewed journals.

As the research progressed, we recognized that this is an emerging field with a relatively limited number of journal articles, particularly on the specific topic of ML in CSCs. Therefore, we later expanded the scope of our search to include "Conference papers" and "Conference reviews", given that many information systems-related research findings are often presented at conferences before journal publication. This was necessary to ensure that the study captured the full breadth of available literature. By mid-2022, we were able to include one relevant conference paper from 2023 in our dataset, reflecting the limited but evolving nature of this field.

Our inclusion criteria were refined to focus on studies that explicitly addressed the circularity of SCs, excluding those that dealt solely with linear SCs without incorporating any CE elements. Additionally, we excluded articles where ML was not a central theme, ensuring the review remained focused on the application of ML within CSCs. Non-English language publications were excluded to maintain consistency and accessibility. This targeted and phased approach allowed us to narrow the extensive literature to a relevant and manageable set of studies, providing a clear understanding of the current state of ML application in CSCs.

### 2.2. PRISMA Protocol

Figure 2 illustrates the PRISMA protocol used in our systematic literature review. The protocol is necessary for ensuring transparency and replicability in the research process, particularly in review articles, where the selection and screening of articles must be clear to the reader. This figure demonstrates the step-by-step process of article identification, screening, eligibility, and inclusion, which is necessary to explain how we arrived at the final set of studies used in the content analysis.

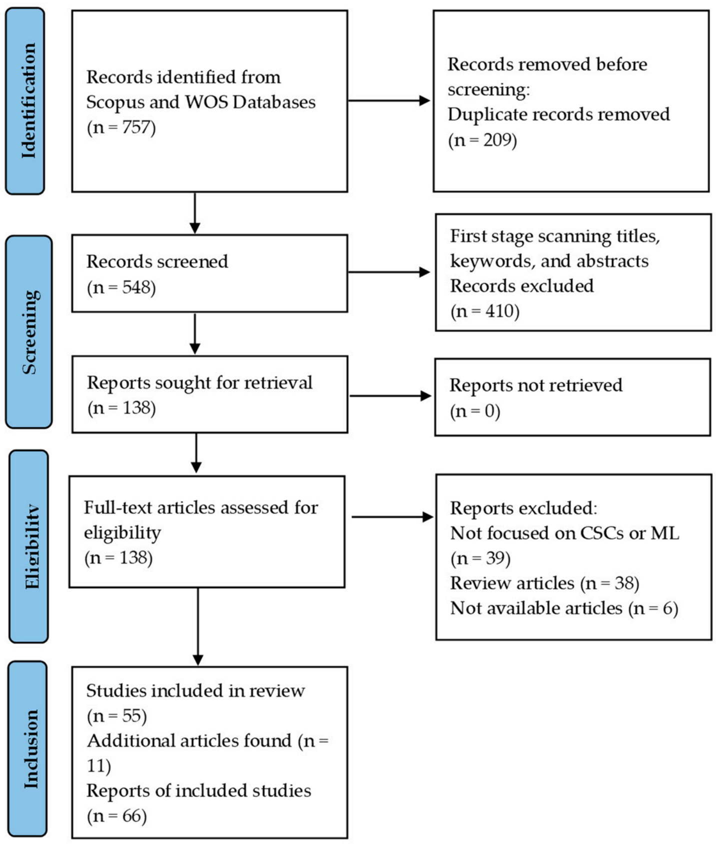


**Figure 2.** PRISMA protocol.

In line with the PRISMA guidelines, we followed a structured and transparent approach throughout our review process to ensure that the study was methodologically sound and that the selection process could be replicated. The initial search across the Scopus and WOS databases yielded 757 articles, including journal and conference papers. After removing duplicates, 548 unique articles remained for further analysis.

**Identification Phase**: During the identification phase, our comprehensive search strategy across the Scopus and WOS databases identified 757 articles, comprising both journal articles and conference papers. Given the emerging nature of the field, we decided to include conference papers alongside journal articles to capture the full breadth of research in ML and CSCs. This was especially important in information systems and related disciplines, where conference papers often present cutting-edge research. At this stage, we systematically removed 209 duplicate records, often occurring when searching multiple databases. After eliminating these duplicates, 548 unique articles remained. This phase ensured that all potentially relevant studies from journal and conference sources were included for further analysis, providing a robust foundation for the screening process.

**Screening Phase**: In the screening phase, we conducted an initial review of the titles, abstracts, and keywords of the remaining 548 articles. The goal at this stage was to quickly identify studies that met our inclusion criteria, which focused on articles that prominently featured both CSC and ML themes. Articles not meeting the thematic focus, such as those addressing general CSs or ML applications without any circularity elements, were excluded. Through this screening, 410 articles were excluded, significantly reducing the pool to 138 for further analysis. This phase helped eliminate studies outside our review's scope, allowing us to focus on articles with clear and relevant contributions to our research question.

**Eligibility Phase**: The eligibility phase involved a full-text review of the remaining 138 articles to ensure they addressed both SC circularity and ML application in sufficient depth. This phase is critical because it ensures that articles included in the final review are thematically relevant and provide substantial and rigorous insights into the topic. During this detailed assessment, 83 articles were excluded for reasons such as:

- Lack of focus on either ML or CSCs,
- Inaccessibility of full-text versions, or
- The inclusion of articles classified as review papers (which, while useful, were outside the scope of empirical research we aimed to review).

After this process, 55 articles remained for the final analysis. This phase ensured that only the most relevant and rigorous studies were included in our final dataset.

**Inclusion Phase**: To ensure the comprehensiveness of our review, we employed a snowballing technique. This involved examining the references and citations of the 55 selected articles to identify any additional relevant studies that might have been missed during the initial search. This process identified 11 more articles, bringing the total number of articles in our final review to 66. These 66 articles were determined to be highly relevant and of high quality, providing a robust foundation for our systematic literature review.

By meticulously following the PRISMA guidelines, we ensured that our review process was both transparent and comprehensive, capturing the most relevant and impactful studies in ML and CSCs. The resulting articles form a solid empirical base for the subsequent analysis and discussion presented in this review.

## 3. Results

### *3.1. Descriptive Analysis*

Visualizations for the descriptive analysis are presented in the following figures, showcasing the trends in ML applications within CSCs across several dimensions. Below are the detailed analyses of each aspect visualized in the figures:

Figure 3 shows the number of publications per year which are included in this study. The year-based distribution highlights a clear upward trend in research studies on ML in circularity. This growth demonstrates the increasing interest in applying ML techniques to enhance CSC practices. However, as the research was conducted in mid-2022, the number of papers for 2022 and 2023 is comparatively lower, not reflecting the full year. Despite this, the significant rise in publications from 2020 to 2021 suggests that ML in circularity is a rapidly expanding research area with the potential for further growth in subsequent years.

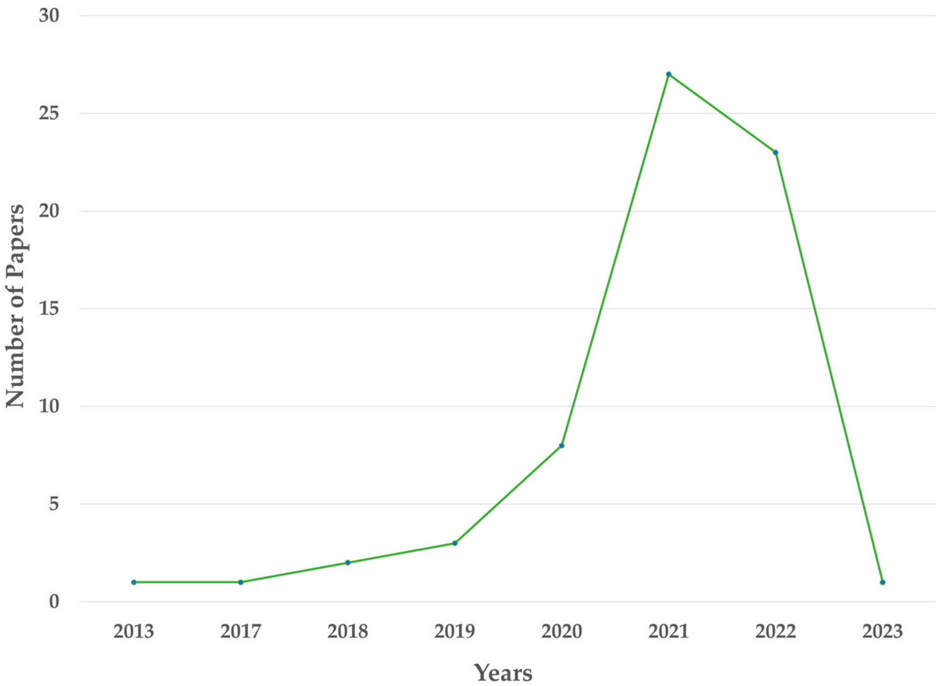


**Figure 3.** Number of publications included in this study per year.

Figure 4 shows the preferred journals for ML in CSCs. The study spans publications from 33 journals, with the Journals of Waste Management, Cleaner Production, and Sustainability representing the top outlets for research in this area. Additionally, many studies are published in conference proceedings and various other journals, highlighting the interdisciplinary nature of ML and CSCs. Conference papers, in particular, are crucial in fields like information systems, where cutting-edge research often emerges first in conferences before journal publications.

Figure 5 shows the ML types used in the selected articles. The types of ML algorithms reveal that supervised learning is the most commonly applied approach, followed by unsupervised learning. This is likely due to the availability of labeled data in CSC processes, making supervised learning a practical choice for classification, prediction, and optimization tasks. In contrast, reinforcement learning is the least utilized, reflecting its still-developing use cases in SC contexts. Algorithms such as Artificial Neural Networks (ANNs), Decision Trees, Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and Deep Learning are among the most frequently employed in the reviewed articles, with ANNs being the dominant choice due to their flexibility and robust performance in complex data environments.

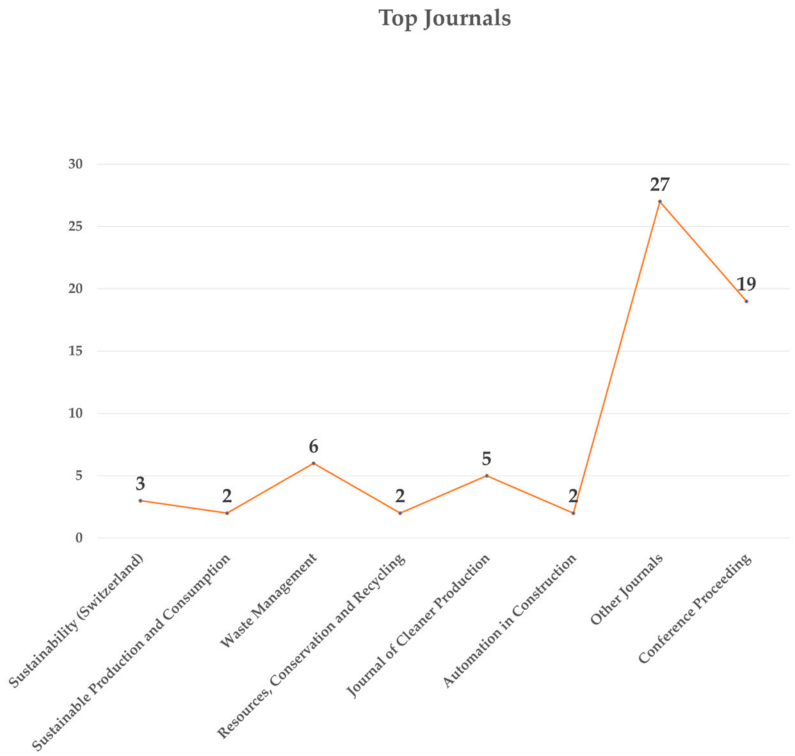


**Figure 4.** Preferred journals for ML and CSCs.

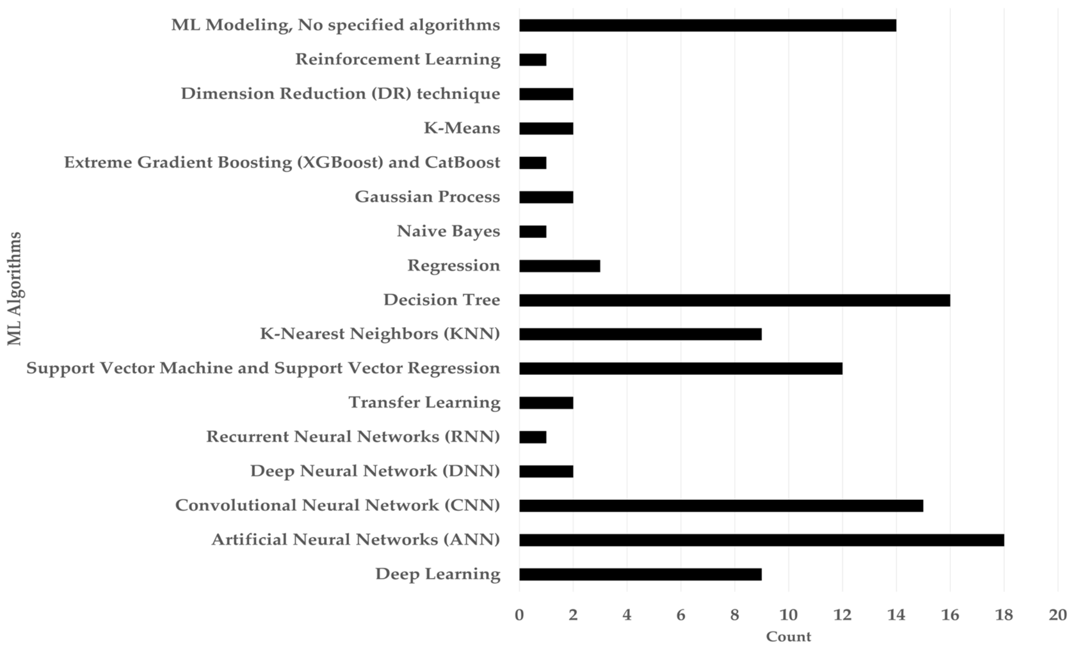


**Figure 5.** ML types used in the selected articles.

We have extracted these methods from many articles, offering future researchers a comprehensive understanding of the available ML techniques applied in CSCs. This collection of methods serves as a foundation for future research to combine or adapt these existing approaches to develop novel and more efficient techniques.

Moreover, based on this analysis, we propose that future research could combine supervised, unsupervised, and reinforcement learning methods to tackle challenges related to data quality, availability, and classification in CSCs. There is also an opportunity to implement novel techniques, such as integrating machine vision and predictive modeling, to enhance the accuracy of waste sorting and resource recovery, which are essential to improving circularity.

Figure 6 shows the research methods employed in the selected articles. Mathematical models emerge as the most commonly used methodology, followed by conceptual methods and mixed methods. This indicates a strong focus on theoretical modeling and simulation in the field of ML and CSCs, often due to the scarcity of real-world case studies and data availability challenges. This lack of empirical studies is a significant research gap, which future studies should aim to address through more practical implementations of ML in CSCs.

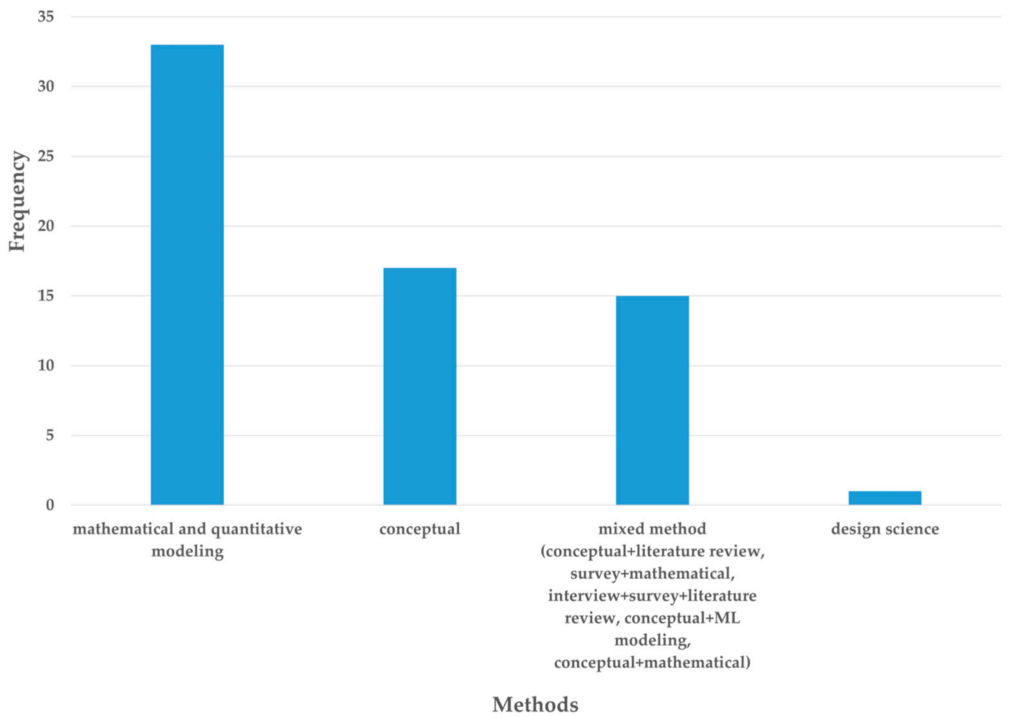


**Figure 6.** Employed research methods in the selected articles.

Figure 7 shows the investigated CSC stages in the selected articles. Research has largely concentrated on the waste management stage of CSCs, indicating that waste management is currently the most prevalent area for applying ML in CSCs. Conversely, the supply, design, and consumption stages have received less attention, suggesting a gap where ML applications could be further developed to optimize resource efficiency and product lifecycle management at these stages.

Figure 8 shows the studied industry types in the selected articles. The analysis of industry types reveals that ML research in CSCs predominantly focuses on household, urban, and municipal waste sectors and the construction and electronics industries. These industries are typically characterized by significant resource recovery and waste management challenges, making them suitable for ML applications. Automotive and plastics industries also feature in the research, though to a lesser extent, indicating opportunities for further exploration of ML in these sectors to promote circularity. Some articles do not specify the industry type or ML algorithms used.

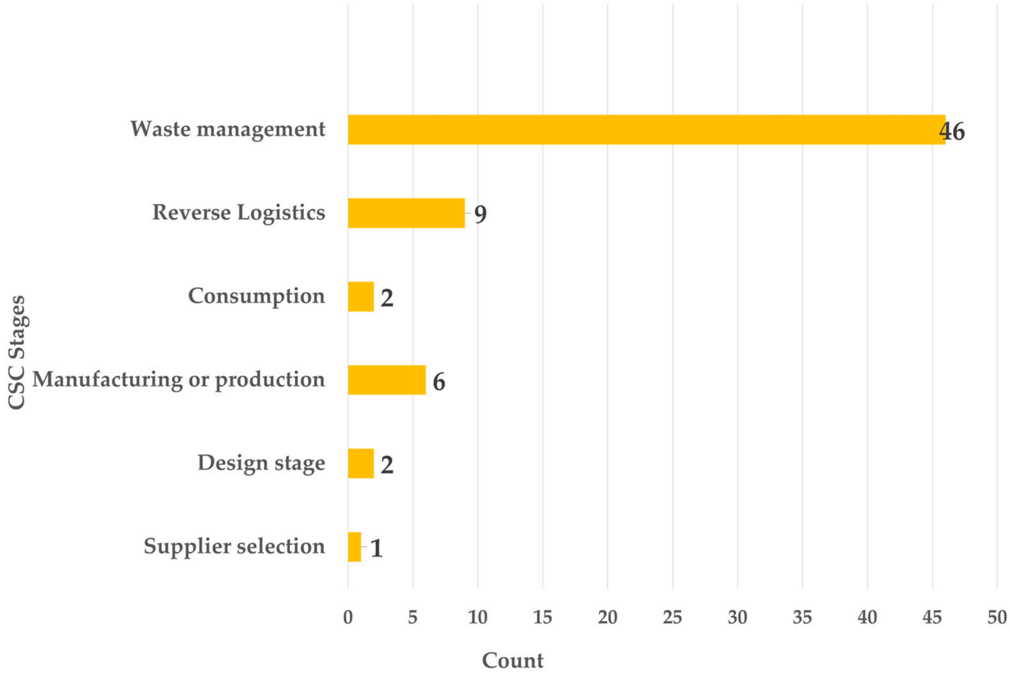


**Figure 7.** Investigated CSC stages in the selected articles.

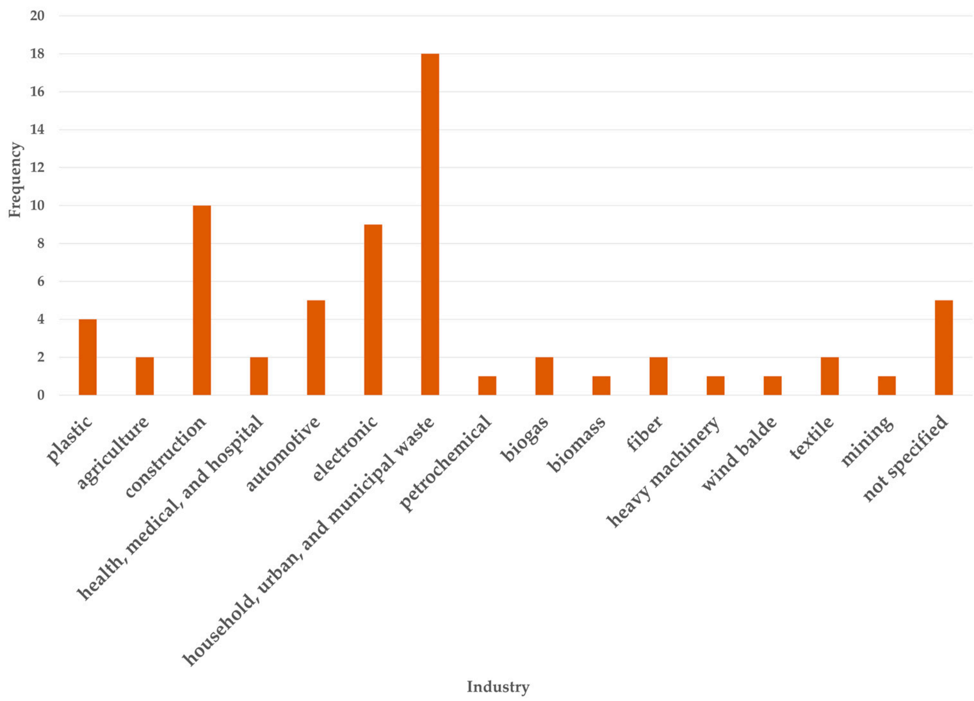


**Figure 8.** Studied industry types in the selected articles.

### *3.2. Content Analysis of ML Technology's Role in Improving SCs' Circularity*

In our content analysis of ML's role in improving CSC performance, we adopt a structured framework to make the application of ML at each stage of the CSC clearer and more precise. This framework, illustrated in Figure 9, includes the following stages: (1) supply, (2) design, (3) manufacturing and production, (4) consumption, as well as the crosscutting stages of (5) forward logistics and waste management, and (6) reverse logistics and waste management [1,2]. We clarify where and how ML supports circularity by breaking down the CSC into these distinct stages.

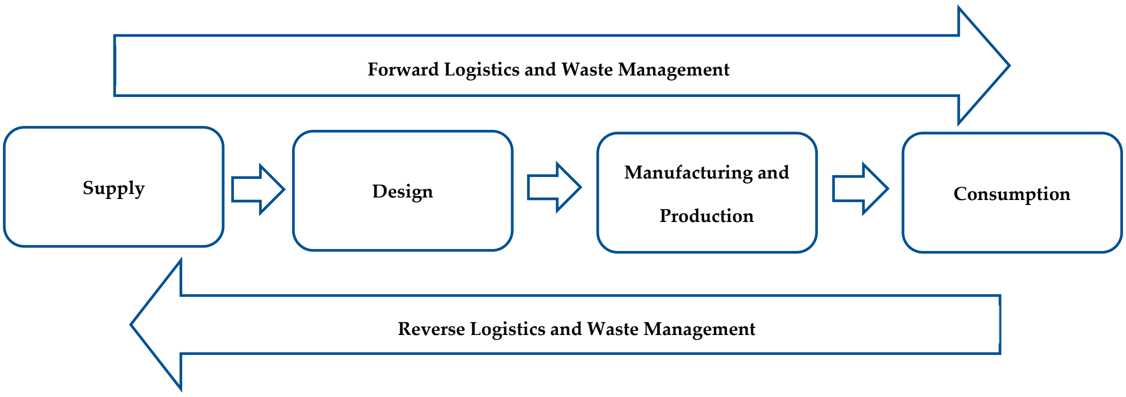


**Figure 9.** Adopted framework based on the stages of CSCs.

Figure 9 visually represents this framework, showing the flow of materials and waste across the CSC. The CS's circularity is highlighted by the integration of forward and reverse logistics, with a focus on waste management in both forward and reverse logistics.

The supply stage focuses on selecting suppliers based on circularity principles. This stage emphasizes the importance of sourcing materials from suppliers that follow sustainable practices, use environmentally friendly resources, and contribute to a CSC. This ensures that the input materials used in production are aligned with CE goals.

The design stage involves designing products with circularity in mind. This includes designing for recyclability, durability, and easy disassembly, ensuring that products can be reused or recycled at the end of their lifecycle.

The manufacturing and production stage refers to the processes involved in transforming raw materials into finished products. In a CSC, manufacturing focuses on optimizing resource usage, minimizing waste, and implementing efficient production processes that align with CE goals. This stage is crucial for ensuring that production operations support the circular flow of materials and energy.

The consumption stage revolves around analyzing and influencing consumer behavior to promote circularity. Companies can design products that align with circular consumption habits, such as reuse and longer product lifecycles, by analyzing consumer preferences and providing insights into product usage. This stage focuses on extending product lifecycles, encouraging responsible consumption patterns, and promoting product sustainability, reuse, or recycling.

The forward logistics and waste management stage deals with moving products from suppliers to consumers, integrating waste management practices throughout the entire SC. This means that at each stage, whether during supply, design, manufacturing, or consumption, forward logistics ensures the efficient transport of materials while minimizing waste.

On the other hand, the reverse logistics and waste management stage focuses on returning used products and materials to the SC for recycling, reuse, or remanufacturing. This stage involves collecting end-of-life products from consumers and sending them back through the SC, either for remanufacturing or extracting valuable materials.

Finally, waste management acts as a crosscutting stage that spans all aspects of the CSC. It includes collecting, transporting, processing, and either recycling or disposing of waste at each stage, whether during supply, design, production, or consumption. Waste management is not confined to one part of the SC but is a continuous process that ensures resources are kept within the loop, supporting circularity throughout.

This framework provides a clear structure for analyzing how CSCs function and how materials flow through various stages. In the following subsections, we will explore the specific role of ML in improving circularity at each of these stages.

#### 3.2.1. ML Application: Supply Stage

Based on the investigated articles, in the case of supplier selection, ML can be used to analyze historical data on suppliers, such as sustainability, delivery times, quality of products, and cost, to identify the best suppliers for a particular company. This can help managers make more informed decisions about which suppliers to use and how to optimize their SC [20]. Likewise, Naz et al. [8] propose implementing ML techniques like ANN to establish a sustainable method of choosing suppliers. Alavi et al. [21] elaborate that ML, the best-worst method, and a fuzzy inference system integrated within a dynamic decision support system can be useful in sustainable supplier selection of CSCs. ML significantly improves and expedites the supplier selection process by efficiently determining the score of each supplier based on various criteria. It achieves this by effectively managing supplier information and synthesizing historical data.

#### 3.2.2. ML Application: Design Stage

According to Laurenti et al. [22], designing products and services with CE principles is important for promoting the recirculation of materials and energy in a CE system. Talla and McIlwaine [23] illustrate using ML applications during the design stage to reduce construction waste and improve recovery, reuse, and recycling efficiency. These applications include forecasting the carbon footprint of building designs, using machine vision to assess asset status and predict system faults, and predicting building energy consumption. Similarly, Płoszaj-Mazurek et al. [24] use ML to develop a model for estimating the carbon footprint of building designs early, which can quickly estimate the total carbon footprint of other projects. Using ML and deep learning techniques, designers can identify potential areas of material waste and develop strategies to minimize this waste through better design choices. This reduces the environmental impact associated with waste generation and encourages the reuse and recycling of materials, thereby contributing to the circular flow of materials within the economy.

#### 3.2.3. ML Application: Manufacturing and Production Stage

As manufacturing advances towards circularity, reducing resource usage during production has become crucial for staying competitive in the sustainable era [25]. Khayyam et al. [26] propose an ML-based approach to improve the circularity performance of carbon fiber manufacturing through waste heat recovery. This includes using ANNs and non-linear regression to predict energy consumption. Similarly, Lopez-Garcia et al. [27] create predictive models using ML algorithms like decision trees, KNN, AdaBoost, gradient tree boosting, and multi-layer perceptron as classifiers that optimize the compounding process for recycled fibers enabling the CE's goals of reducing waste and conserving resources. Chiu et al. [28] use ML to redefine the key factors and improve the prediction of biogas generation output, resulting in a more accurate prediction model.

Prioux et al. [29] use unsupervised ML algorithms to assess and evaluate different life cycles and biomass pre-treatment processes for glucose production. Vondra et al. [30] use ML techniques to improve circularity in treating liquid digestate from biogas production. They use Monte-Carlo simulation and ANN to find the best implementation pathways for an evaporator system. Finally, González Rodríguez et al. [31] investigate the use of ML-based decision-making in production planning under uncertainty, which can improve manufacturing efficiency by making scheduling task decisions and avoiding collapses that may occur under human decision-making.

#### 3.2.4. ML Application: Consumption Stage

Moving towards a CE necessitates changes in consumer behavior, which can be accomplished through awareness campaigns and education on sustainability. ML algorithms, such as SVM in conjunction with simulation techniques, have been used to examine how a population of consumers adopts products (in this case, washing machines) designed with circularity approaches [32]. Moreover, Shahidzadeh et al. [33] acknowledge that deep learning can predict a product customers' emotions regarding used products through social media posts to help managers make decisions about returned products to be reused, recycled, remanufactured, etc., which results in reducing returned products and waste as well as increasing customers' loyalty.

#### 3.2.5. ML Application: Logistics Stage

Reverse logistics, in combination with traditional logistics, which includes coordinating the transportation, storage and warehousing, and inventory management of goods from suppliers to customers, has been identified as crucial for promoting circular development [34]. Monteiro et al. [35] propose using ML with IoT, blockchain, and gamification to monitor and analyze agrochemical products and packaging disposal along the reverse SC. Zec et al. [36] employ ML to create predictive models estimating the residual value of second-hand items in circular business models. Their approach mitigates financial risks, encouraging the transition to circular models and fostering environmental sustainability by reusing and recycling materials such as clothing. Accurate value estimations promote investor confidence, facilitating the shift from linear to CEs.

Gayialis et al. [37] harnessed the power of ML, IoT, and cloud computing to enhance the accuracy of equipment maintenance predictions within the realm of service SC logistics. Their approach supports the optimization of reverse SC operations by accurately forecasting equipment failures and maintenance needs. The researchers tested their model in a case study involving washing machines and refrigerators, serviced and maintained by the same companies, to demonstrate its practical applicability. Similarly, using digital twin models, Zacharaki et al. [38] use ML to support CE by predicting maintenance needs and potential faults of large industrial equipment.

Briese et al. [39] utilize ML, particularly deep learning and CNNs, for accurate image-based recognition of parts in reverse logistics and the remanufacturing of SC, enhancing efficiency and reducing waste. Lehr et al. [40] utilize machine vision with SVM and CNN in deep learning algorithms to create a mobile app for automotive reverse logistics. The app collects images of faulty parts, connects users to suitable spare parts via an identification web service, and enables seamless ordering or remanufacturing of parts. Similarly, Stavropoulos et al. [41] apply ML technology in identifying automotive defective parts and determining whether these parts can be remanufactured. This is achieved through the use of CNNs that are trained to analyze images of damaged automotive frames. These CNNs can distinguish between parts that can be remanufactured and those that cannot. By accurately identifying which parts are suitable for remanufacturing, ML technology optimizes the usage of resources and reduces waste.

Schlüter et al. [42] highlight the vital role of ML in streamlining the identification, inspection, and sorting of returned automotive components. They develop an approach for visual object recognition, eliminating manual input and improving accuracy. ML automates inspections, enhancing standardization and objectivity by detecting defects and damages that may evade human inspectors. Lickert et al. [43] use ML to analyze and categorize data related to returned automotive parts in order to predict the condition of these parts for remanufacturing. They use different ML algorithms such as KNN, SVM, decision trees, and neural networks to assist in selecting suitable algorithms for classification tasks in reverse logistics.

#### 3.2.6. ML Application: Waste Management Stage

Waste management within CSCs is considered critical for extracting the maximum value from a product through the recycling of used components and materials, which has significant economic and environmental benefits [2]. ML algorithms have been useful in various end-use activities within different construction industries, municipal and household waste, E-waste, etc.

Construction Industry

Recent studies have focused on developing ML models to enhance waste management practices in the construction industry. For instance, neural networks of ML can estimate recycling, repurposing, and waste produced during demolition stages [23,44]. Additionally, deep learning can be used to classify different types of waste by analyzing container images. Davis et al. [45] propose the use of automated classification of construction and demolition waste on worksites to enhance productivity, reduce construction costs, and facilitate increased reuse or recycling of construction waste. They designed a model using CNN to classify images of various construction and demolition waste classes deposited in waste bins. Hoong et al. [46] developed CNN to classify images of recycled aggregates based on their composition.

Aknabi et al. [47] developed a deep-learning model to predict the amount of salvage and waste materials that can be obtained from buildings before demolition. Rakhshan et al. [48,49] develop probabilistic models using supervised ML techniques to predict the technical and economic reusability of load-bearing building elements at the end-of-life of a building. Their approach determines the factors affecting the reuse of building structural elements. Moreover, ML has been used to estimate construction waste generation [50]. The authors use ANN with multiple linear regression, decision trees, and grey models to compare the strengths and weaknesses of waste quantification models in terms of accuracy, scalability, and explanatory clarity. Finally, Wu et al. [51] use ML to predict the presence of hazardous materials in buildings. Their proposed ML approach targets in situ hazardous material management and could support decision-making regarding risk evaluation in selective demolition work.

Households and Municipalities

ML has been applied to household and municipal waste management. Zaman [52] develops and tests an ML model to predict, identify, and measure household waste contaminations and suggests ways to improve waste recycling. In the article of Cîmpeanu et al. [53], ML technology plays a crucial role in the development and implementation of chatbot solutions (A.I.R-e and Iio) to enhance the performance and effectiveness of these chatbots, enabling them to perform tasks related to municipal waste recycling, waste sorting, and providing relevant information to users. Lühr et al. [54] show how an ML-based application enhances waste collection in the Municipality of Valdivia, Chile. The technology enables the estimation of waste collection trucks' future trajectories, providing real-time updates and estimated arrival times. This feature empowers residents to plan waste disposal effectively, minimizing waste dispersion and optimizing the waste collection process.

ML is also used to study factors affecting municipal solid waste production, separation, and costs [55]. Fasano et al. [56] use deep learning models to identify the most influential variables and their effects on municipal solid waste production. Mohammed et al. [57] apply ML to create a digital model that sorts and classifies waste using an ANN and features fusion techniques. Chen [58] develops an automated waste recycling framework with ML and IoT that can separate materials in a mixed recycling application, and Gue et al. [59] use ML to generate rule-based models that reveal the impact of city and country attributes on waste management performance.

Furthermore, ML enhances waste classification from images, which is vital for waste management systems. Nnamoko et al. [60] use ML to increase the accuracy of image-based waste classification. Wilts et al. [61] use a robot with computer vision and deep learning to sort and segment municipal solid waste. The robot achieves high purity but low materials recovery due to the waste composition. Paulauskaite-Taraseviciene et al. [62] use ML techniques to forecast municipal solid waste generation and composition. Fan et al. [63] and Rosecký et al. [64] use ML to predict municipal solid waste generation and fractions while assessing various factors affecting the generation of waste fractions at different territorial levels. Wang et al. [65] propose a system to achieve high accuracy waste classification at the start of garbage collection, separating the recyclable waste into six categories using deep-learning CNN and IoT devices to enable real-time monitoring of the total amount of waste produced and the status of any waste container. Kontokosta et al. [66] present an analytical approach that combines small area estimation techniques with ML algorithms to predict weekly and daily waste production at the building level to estimate refuse and recycling tonnages for over 750,000 residential properties in New York City.

Similarly, Kannangara et al. [67] utilize ML algorithms to build models projecting municipal solid waste generation and diversion. They leverage census data at regional and municipal levels, finding that neural network models achieve 72% accuracy for waste generation and 32–36% accuracy for paper diversion. Their study aims to improve waste prediction accuracy and identify key socio-economic factors driving waste generation and diversion patterns. Meza et al. [68] also utilize ML algorithms to forecast urban solid waste generation in Bogotá, Colombia. Their study provides efficient alternatives for planning and designing waste collection, transport, and disposal technologies in urban areas while considering their unique characteristics. Magazzino et al. [69] use an ANN technique and time series to examine the causal link between wealth, urbanization, waste generation per capita, and GHG emissions in Denmark.

Electrical Equipment and Electronics

Abou Baker et al. [70] use ML, particularly transfer learning, to classify E-waste (e.g., smartphones and electric screwdrivers) to increase circularity. The system maximizes material recovery rates and enhances classification performance with minimal human intervention. Similarly, Cabri et al. [71] utilize ML, including YOLOv5 and CNN algorithms, for sorting electronic components for recycling purposes. ML enables material sorting based on component type. They also implement a real-time edge system for immediate feedback and decision-making during recycling, enhancing resource utilization. D'Morison et al. [72] apply ML algorithms, including KNN, SVM, and neural networks, to automate the detection of fill levels in bins for Nokia's Take-Back initiative. Their image processing technique combined with ML determines the fill levels, optimizing the collection of disposed mobile phones and accessories.

Johnson et al. [73] utilize ML and computer vision in the RoboCRM system, enabling automatic detection, identification, and sorting of battery-powered devices and batteries from E-waste. ML algorithms, including CNNs, analyze optical data to distinguish between powered and unpowered E-waste, facilitating efficient recovery of critical raw materials like lithium, cobalt, and nickel for reuse in manufacturing. Similarly, Basia et al. [74] utilize ML to estimate the State of Health (SoH) of Lithium-ion (Li-ion) batteries, which is essential for their repurposing. ML technology creates correlation models linking battery parameters to SoH, a critical health indicator determining reuse potential. ML algorithms, including linear regression, support vector regression, and feed-forward neural networks, learn the correlations between battery characteristics and SoH, aiding in determining suitable second-life applications and prolonging battery lifespan for less demanding energy storage purposes. Finally, Poschmann et al. [75] utilize neural network ML algorithms to aid in decision-making for optimal end-of-life utilization of product components, considering factors such as life-cycle data and material composition. Their system determines whether components should be reused, recycled, or disposed of.

Other Industries

Various industries are exploring the use of ML to address the issue of waste and promote circularity. For instance, Deng et al. [76] utilize SVM for ML-based classification, determining the economic feasibility of recycling end-of-life products. Accurate waste prediction in the Polish automotive industry aids in material return planning, minimizing environmental impact by using ANN with fuzzy logic (neuro-fuzzy systems) to forecast waste at various supply, production, and distribution stages [77]. Majchrowska et al. [78] train neural networks with over ten open-source waste databases to detect and classify waste into seven main categories. They propose a deep learning-based framework to localize trash in the image and identify its class using two separate neural networks. Nañez Alonso et al. [79] use CNN to categorize images of waste materials into four classes based on their composition. Gruber et al. [80] propose using imaging fluorescence spectroscopy with ML or deep learning classification algorithms to improve the accuracy of plastic particle classification. Chin et al. [81] apply ML to enhance the classification of plastic waste by leveraging metal contamination data.

Salim et al. [82] utilize ML to create the plastic reuse reminder system, prompting individuals to reuse plastic bottles instead of disposing of them as waste. The system employs the Single Shot Multibox Detector (SSD) with MobileNetV1 for real-time object detection of reusable plastic bottles near trash bins. Chin et al. [83] employ ML to evaluate the recyclability of plastic waste. They categorize the quality trends of contained polymers with auxiliary materials using an ML framework that models the qualities of plastic waste and creates a centralized database to identify the qualities of plastic waste from different plants.

Barraza et al. [84] propose an approach to optimize the location of hubs for transporting mining waste materials. Their methodology combines K-means, data mining techniques, and multi-criteria decision-making methods to address the challenge of processing mining waste materials. Walzberg et al. [85] analyze the potential effectiveness of CE interventions for end-of-life wind blades. Yatim et al. [86] predict the higher heating value of biomass waste using ANN and linear regression models based on ultimate analysis data.

Kumar et al. [87] develop a solution for sorting COVID-related medical waste streams from other waste types. Rudisch et al. [88] employ ML, particularly CNNs, to analyze the spectroscopic data obtained from textiles. Their approach classifies different materials and their compositions to improve sorting precision and efficiency, which are critical to improving circularity in the textile sector. Finally, Serrano-Munoz et al. [89] explore using reinforcement learning algorithms in contact-rich disassembly tasks.

Table 1 provides an overview of the most significant applications of ML in CSCs across key industries examined in this study. It highlights industry-specific challenges and opportunities, clearly comparing how ML can address critical issues such as waste management, energy consumption, and resource recovery. This summary aims to contextualize the varied impacts of ML on different sectors, demonstrating its potential for enhancing sustainability and circularity in diverse operational environments.

**Table 1.** Summary of ML applications, challenges, and opportunities in studied key industries for CSCs.

| **Industry** | **ML Applications** | **Challenges** | **Opportunities** |
|---|---|---|---|
| Construction | Energy consumption prediction and sustainable design, predicting waste generation and material recovery, waste sorting | Low-quality data, limited access to structural data, overfitting of datasets | Analyzing construction designs and predicting aspects such as the carbon footprint, energy consumption, and potential material waste during the design phase. Estimating recycling, repurposing, and the waste produced during construction and demolition stages in the construction industry. Classifying different types of rubbish through digital images collected from worksite containers in the construction industry. |

**Table 1.** *Cont.*

| Industry | ML Applications | Challenges | Opportunities |
|---|---|---|---|
| Household and municipal | Predicting waste generation, waste sorting | Unstructured data, inconsistent waste management practices across municipalities | Developing predictive models that can accurately forecast the future generation of municipal waste. By leveraging historical data and relevant variables such as population growth, consumption patterns, and waste production trends, these models can provide valuable insights for efficient resource allocation and effective waste management strategies within the CSC. Classifying waste in smart cities. Efficiently sorting municipal waste in smart cities. Enabling the efficient extraction of recyclable materials from the municipal waste stream. |
| Electronic | E-waste evaluation for repurposing, E-waste collection and monitoring, E-waste sorting | Complexity in sorting, limited availability of data on product composition | Estimating the State of Health (SoH) of Lithium-ion (Li-ion) batteries in E-waste. Predicting fill levels in the bins by integrating a lightweight image processing technique with ML. E-waste classification and systematically identifying and segregating electronic waste materials. |
| Automotive | Identifying and predicting automotive defective parts condition, predicting generated waste | Difficulty in classifying defective parts for remanufacturability, data availability, and quality issues for accurate ML predictions | Classifying automotive defective parts and determining their remanufacturability. Anticipating the quantity of waste produced during various stages of production. |

### *3.3. Challenges of ML Usage in CSCs*

Based on the content analysis of the reviewed articles, there are several challenges, limitations, and barriers to the effective use of ML in CSCs. Zaman [52] identifies data privacy and initial investment as primary barriers to developing ML models. One of the key concerns with data privacy is the vast amount of sensitive information collected by ML systems, including business-critical data and potentially sensitive consumer information. If not properly protected, these datasets can be vulnerable to breaches or misuse, raising ethical concerns about data handling. To mitigate these risks, CSs need to adopt stringent data protection protocols, such as encryption, access control, and anonymization.

Security concerns are equally important, as ML systems can become cyberattack targets. The increased reliance on data-driven decision-making exposes SCs to potential breaches that could lead to the theft of proprietary information or the manipulation of ML algorithms. Security measures must be enhanced, such as using secure data storage, blockchain for data integrity, and multi-factor authentication, to ensure the safe operation of ML technologies in CSCs.

Other challenges identified in the literature include limited input data, unbalanced input data classification, and a shortage of skilled employees to develop and manage ML models [90]. Furthermore, ML-based decision-making and predictions can yield unexpected results, especially in the case of rare events [31]. These can be addressed through retraining algorithms or setting up alarms to flag anomalies.

In the construction sector, for example, ML faces limitations such as low-quality data, overfitting of datasets, and hard-to-access structural building-specific data [51]. Similarly, Nnamoko et al. [60] highlight the high computational cost of using CNNs for image classification, which results in longer development times and larger prediction model sizes. Additionally, the lack of transparency in experimental setups in previous studies impairs the comparability of results and limits reproducibility.

Conventional waste separation methods still rely heavily on manual sorting, which is error-prone due to limited knowledge of waste classification. ML-based automation in waste management has great potential but faces data availability and interpretation challenges. In remanufacturing, Serrano-Munoz et al. [89] point out the need for flexible and robust autonomous systems that handle uncertainties and complexities in product conditions, process planning, and operation. Moreover, the lack of exploration and application of reinforcement learning algorithms in disassembly tasks presents an additional limitation.

Overall, using ML techniques in CSCs faces challenges related to data availability, large dataset acquisition, complex model interpretation, and significant privacy and security concerns [62]. Addressing these challenges will require the development of more robust data security protocols, transparent ML models, and improved infrastructure for collecting and managing high-quality data in CSCs. Mirzahossein et al. [91] demonstrate the use of hybrid ML models, combining deep learning methods like Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM) networks with wavelet noise reduction techniques to improve prediction accuracy under noisy data conditions. While this study focuses on traffic volume prediction, the approach of combining multiple ML techniques to handle data quality issues and improve model accuracy can be adapted to other sectors, including CSCs, where similar data challenges exist.

## 4. Discussion

Next, we discuss the general observations that we can make from our study and synthesize our findings in the form of general propositions. First, we address our main research question and discuss the role of ML in enhancing efficiency and effectiveness across CSC states. Next, we delve into the transformative impact of ML on SC configuration for circularity, synergistic enhancement of CSC performance through ML and complementary technologies, advancing circularity in CSCs through direct and collaborative ML applications. Finally, we discuss the contribution of ML-driven circularity to broader sustainable SC management.

*Synthesis and General Propositions*

**Proposition 1.** *The use of ML improves efficiency, effectiveness, or both at various stages of CSCs.*

**Justification.** This study showed that ML plays a pivotal role in enhancing both the efficiency and effectiveness of CSCs across various stages. By analyzing historical supplier data, ML aids in sustainable supplier selection and optimizing SC operations [8,21]. In the design phase, ML forecasts carbon footprints and energy consumption [23,24], aligning product designs with CE principles. ML optimizes resource usage during manufacturing, reducing environmental impact [26,27]. ML influences sustainable consumer behavior in consumption and improves decision-making for product returns, fostering customer loyalty [32,33]. For reverse logistics, ML optimizes reverse logistics operations in the service SC and achieves effective sorting and recycling of waste products [37,41]. At the waste management stage, ML-based waste prediction and classification promote sustainable and circular practices [23,44–46,50,52,55,57,60–68,70,73,77–81,87,88].

From these observations, we can conclude that the ML applications at the supply, design, and manufacturing stages are more focused on efficiency, aiming to optimize processes, reduce waste, and improve decision-making. On the other hand, the ML applications at the consumption, logistics, and waste management stages are more focused on effectiveness, aiming to foster sustainability, improve decision-making, and optimize resource recovery to promote circularity.

**Proposition 2.** *The integration of ML into each stage of CSCs transforms the overall SC configuration, enhancing circularity.*

**Justification.** The findings of our literature study showcased several examples where the application of ML in one CSC stage affected other CSC stages, promoting circularity of the whole CSC. For instance, ML predictions in the design phase foster material recovery and reuse in the waste management phase [23,24]. ML use in design, specifically in predicting aspects such as material waste, will positively correlate with increased material recovery and reuse. ML-driven forecasts empower designers to make choices that minimize waste generation, contributing to the circular flow of materials within the economy. These ML-driven predictions in the design phase aim to minimize and reduce material waste. Armed with insights from ML forecasts, designers can identify potential areas of material waste and develop strategies to minimize waste through better design choices. By doing so, they contribute to the circular flow of materials within the economy.

The manufacturing and production stage witnesses a transformation in resource usage and waste reduction through ML-based approaches. Predictive models and classification algorithms optimize manufacturing processes, impacting the configuration of production operations. ML contributes to a more circular configuration by minimizing waste and conserving resources [26,27].

Consumer behavior is analyzed at the consumption stage through ML algorithms predicting the adoption of sustainable products [32,33]. ML's prediction about consumer choices and emotions alters the configuration of marketing strategies, aligning them with circular principles and influencing purchasing patterns towards more sustainable options.

Forward and reverse logistics undergo configuration changes due to ML applications. ML, combined with technologies like IoT and blockchain, enhances monitoring and analysis in logistics operations [35,37]. This results in a more optimized transportation, storage, and inventory management configuration, aligning with circular objectives.

The waste management stages see significant changes in configuration through ML. ML models predict, classify, and optimize waste handling processes, impacting the entire configuration of waste management practices. This includes improvements in recycling, repurposing, and reducing waste, leading to a more circular and sustainable waste management configuration.

In summary, ML's integration at each stage brings about transformative changes in the configuration of CSCs. It introduces data-driven decision-making, optimization, and sustainability considerations, fundamentally altering the traditional SC configurations towards a more circular and efficient model.

**Proposition 3.** *The combination of ML with complementary technologies like IoT, blockchain, and computer vision leads to enhancement in performance across CSC.*

**Justification.** The content analysis highlights instances where ML is coupled with various technologies such as IoT, blockchain, computer vision, robotics, etc. For example, in the logistics stage, ML is combined with IoT and blockchain to monitor and analyze the disposal of agrochemical products, optimizing reverse SC operations [35]. This combination of ML with IoT and blockchain brings a broader perspective to SC visibility and traceability, contributing to higher performance by ensuring transparency and efficiency in material flows.

In the reverse logistics stage, ML is integrated with cloud computing and IoT to enhance the accuracy of equipment maintenance predictions [37]. This combination provides a comprehensive approach to predictive maintenance, ensuring higher performance in terms of minimizing downtime and optimizing resource utilization.

Moreover, ML is coupled with computer vision and deep learning in waste management stages for image-based recognition of parts and waste classification [61]. These combinations lead to broader capabilities in recognizing and categorizing different materials, contributing to higher performance in sorting and recycling operations.

Also, reinforcement learning of ML in robotics facilitates contact-rich disassembly [89]. Organizations exploring reinforcement learning algorithms, such as Q-Learning, in contact-rich disassembly tasks will experience facilitated and automated disassembly processes. ML-driven robotics optimize the handling and recycling of components and materials, aligning with CE principles and promoting responsible waste management within the CSC.

Therefore, the proposition is justified as the content analysis consistently demonstrates that the synergy between ML and other technologies results in a broader scope of applications and higher performance across different stages of CSCs. The combined use of these technologies brings about comprehensive solutions that address multiple aspects of SC operations, contributing to improved efficiency and effectiveness.

**Proposition 4.** *Firms can advance their circularity goals through both direct applications of ML and through collaboration with other ML-driven firms.*

**Justification.** Throughout the content analysis, examples illustrate how firms can leverage ML directly or through collaboration with other firms to enhance circularity within the SC. In the supply stage, firms utilize ML for sustainable supplier selection, predicting and classifying suppliers based on their sustainability scores [21]. This direct usage of ML enables firms to make more informed decisions about supplier selection, optimizing their SCs for sustainability.

Furthermore, the content analysis mentions the use of ML in predicting consumers' adoption of sustainable products and understanding their emotions towards used products in the consumption stage [32,33]. Firms can directly apply ML techniques to analyze consumer behavior and tailor their strategies for promoting circular products. Alternatively, collaboration between firms in the consumption and design stages can involve sharing ML-driven insights to align product designs with consumer preferences, thereby enhancing circularity.

In summary, the content analysis provides examples of both direct usage of ML by individual firms and collaboration among firms in the SC. Whether through direct adoption or collaborative efforts, ML is a tool for firms to enhance their circularity purposes, making SC operations more sustainable and efficient.

**Proposition 5.** *ML applications for circularity purposes within SCs advance the broader sustainability agenda.*

**Justification.** As an essential component of sustainability, circularity involves minimizing waste, reusing materials, and fostering responsible resource management. ML applications that enhance circularity inherently contribute to the broader sustainability agenda within SCs. ML's ability to analyze consumer behavior, predict equipment failures, and optimize logistics further supports the comprehensive sustainability goals of SC management.

As ML applications extend beyond circularity, addressing areas such as waste sorting, energy consumption prediction, and sustainable product design, the concept of sustainable SCs becomes more encompassing. ML's role in achieving predictive maintenance, reducing energy consumption, and facilitating responsible waste management aligns with the three pillars of sustainability—environmental, social, and economic aspects.

Moreover, the long-term sustainability of ML applications in CSCs will be driven by technological advancements and innovations such as technology readiness and machine vision in waste sorting. These technologies will improve the precision and efficiency of waste management processes, enabling better resource recovery and further reducing environmental impacts over time. As market dynamics evolve, ML applications will also adapt, ensuring that CSCs remain at the forefront of sustainable practices.

In essence, ML's usage for circularity purposes serves as a catalyst for a broader transformation towards sustainable SCs. The integration of ML technologies allows SCs to not only optimize circular practices but also embrace a more holistic and responsible approach to their environmental, social, and economic impact. Thus, the proposition holds that ML, when applied strategically for circularity within SCs, contributes significantly to the evolution of sustainable SC practices and ensures their long-term viability through continued technological innovation.

## 5. Conclusions

ML technologies emerge as an important enabler offering the potential to enhance circularity across SCs through predictive analytics, sustainable policy guidance, and informed decision-making across the full range of SC stages, thus including design, production, consumption, logistics, and waste management. Notably, our findings underscore the potential of supervised ML algorithms, particularly ANN and deep learning algorithms, decision trees, and SVM in waste management stages within CSCs. This indicates that ML can optimize waste management and recycling processes, reducing waste generation while bolstering circularity.

Despite growing research interest in ML applications in CSCs, we argue that the research is still in its infancy, and there remains a relative paucity of research addressing the opportunities of enhancing circularity through ML. Next, we discuss future research possibilities at each stage of the CSC.

### *5.1. Further Research Avenues*

Supply stage—Demand Forecasting for Circular Products and Optimization of Material Flow. Accurate demand forecasting is crucial in a CSC. Further research can focus on how ML can analyze trends, historical data, and market dynamics to predict the demand for products made from recycled materials or designed for longevity and reuse. This would help align procurement with actual market needs, reducing waste and overproduction. Further research could also explore how ML can optimize the flow of materials, including recycled and recyclable materials, to ensure efficient use and minimal waste. By analyzing the lifecycle of materials and products, ML algorithms can suggest the most sustainable options for material procurement, including identifying opportunities for using recycled materials.

Design Stage—Designing Recyclable Products. A significant research gap exists in how ML can contribute to designing recyclable products. The integration of ML into the design phase holds promise for developing products with an extended lifecycle and enhanced recyclability. For instance, in the textile industry, ML could be utilized to predict the longevity and recyclability of different fabric blends, enabling designers to make more informed choices about materials. In the automotive sector, ML can aid in analyzing various design parameters to create vehicles that are easier to dismantle and recycle. Future research should focus on developing ML models that can effectively integrate environmental considerations into the design process, paving the way for a more sustainable approach to product development.

Manufacturing Stage—Optimizing the Use of Recycled Materials. The manufacturing stage presents opportunities for ML to optimize the use of recycled materials across various industries. For example, in the steel industry, ML algorithms could predict the quality and performance outcomes of using different proportions of recycled steel, thus informing more efficient production processes. Current research is limited in exploring how ML can be used to dynamically adjust manufacturing processes based on the availability and quality of recycled materials. Further studies could focus on developing predictive models that seamlessly incorporate recycled content into production cycles, ensuring quality and environmental sustainability.

Consumption Stage—Predicting Consumer Recycling and Product Returns. At the consumption stage, the potential of ML to predict consumer recycling and product returns remains underexplored. Understanding these patterns is crucial for businesses to optimize their reverse logistics and plan subsequent steps. ML algorithms can analyze consumer data to identify trends in product usage, return rates, and recycling behaviors, enabling companies to tailor their strategies accordingly. Research in this area could lead to more efficient resource allocation, waste reduction, and enhanced consumer engagement.

Reverse Logistics Stage—Optimizing Transportation and Inventories. In the realm of reverse logistics, a critical research gap exists in utilizing ML to optimize transportation and inventory management in the reverse SC. ML could be pivotal in forecasting the volume of returned goods, thus aiding in efficient transportation planning and inventory management. This optimization is particularly relevant for sectors with high return rates, such as e-commerce. Future research should investigate ML algorithms capable of predicting the flow of goods in reverse logistics.

Waste Management Stage—Automating Waste Sorting. Finally, there is a pressing need to further examine ML's role in automating waste sorting at the waste management stage, specifically for challenging materials like textile waste. Current methods of waste sorting are often labor-intensive and less efficient. Implementing ML algorithms in this stage could revolutionize waste management by automating the sorting process, increasing efficiency, and reducing human error. Research should focus on developing sophisticated ML models that can accurately identify and sort a wide range of waste materials, contributing significantly to sustainability efforts.

Enhancing Efficiency and Effectiveness: Future research could explore the role of ML in improving the efficiency and effectiveness of CSCs by examining real-world case studies. For example, there is an opportunity to investigate how ML applications in CSCs have contributed to enhancing recycling rates or expediting supply chain processes.

Collaborative Utilization of ML: Future studies may investigate the comparative advantages of collaborative ML initiatives among firms versus individual adoption within CSCs. This research could analyze various dimensions, including economic viability and contributions to circularity objectives. By examining these aspects, insights can be gained into the most effective approaches for leveraging ML within CSCs, whether through collaborative efforts or individual implementations.

Our review highlights the significant role of mathematical modeling and conceptual analyses in demonstrating ML's potential to promote circularity in CSCs. However, the lack of real-world case studies limits our understanding of how ML can be effectively applied in practical settings. Future research should focus on incorporating case studies in real operating environments to provide deeper insights into the business, environmental, and societal impacts of ML in CSCs. These empirical studies are crucial for validating theoretical models, uncovering challenges, and offering actionable insights for businesses looking to adopt ML-driven circularity strategies. By doing so, we can better understand how ML technologies can be scaled, integrated, and optimized to enhance the efficiency and sustainability of CSCs.

Future studies can focus on the empirical measurement of ML's impact on CSCs by developing comprehensive frameworks that combine qualitative and quantitative indicators. These could include tracking operational efficiency improvements, waste minimization efforts, and resource recovery rates to better understand ML's contribution to circularity strategies. Moreover, researchers should consider conducting real-world case studies to validate these metrics and offer practical insights into how ML can drive circularity across various industries.

### *5.2. Practical Implications*

This review highlights the versatility of ML in promoting circularity and sustainability across diverse industries and stages of SC. The examples presented in this review serve as valuable insights for policy-makers and decision-makers, shedding light on the immense potential of ML in advancing sustainability and circularity. ML has been successfully applied in environmental and CE policies within firms, such as using ML-based classifications to determine the viability of recycling end-of-life products. Furthermore, ML can also play a crucial role in shaping consumer behavior through awareness campaigns and educational initiatives.

The choice of the ML algorithm should align with the specific objectives and setting of the use case, as well as the type and volume of available data, while considering the unique context and purpose. The reviewed studies provide evidence of ML's effectiveness in providing policy advice, such as supplier selection. By leveraging historical supplier data, ML can assist in identifying the most suitable suppliers for a company, enabling more informed and sustainable decision-making processes.

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