Challenges and Opportunities of Artificial Intelligence and Machine Learning in Circular Economy

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Abstract

The inherent "take-make-waste" of the current linear economy is a major contributor to exceeding planetary boundaries. The transition to a circular economy (CE) and the associated challenges and opportunities requires fast, innovative solutions. Artificial Intelligence (AI) and Machine Learning (ML) can play a key role in the transition to a CE paradigm by overcoming the challenges of increasing material extraction and use and creating a far more environmentally sustainable future. This article's objective is to provide a status quo on the use of AI and ML in the transition to CE and to discuss the potential and challenges in this regard. The literature survey on Google Scholar using targeted queries with predefined keywords and search operators revealed that the number of experimental scientific contributions to AI and ML in the CE has increased significantly in recent years. As the number of research articles increased, so did the number of ML methods and algorithms covered in experimental CE publications. In addition, we found that there are 84% more AI and ML-affiliated research articles on CE in Google Scholar since 2020, compared to the total number of related entries, and 55% more articles since 2023, compared to the related articles up to 2023. The status quo of the scientific contributions shows that AI and ML are seen as extremely useful tools for the CE and their use is steadily increasing.

Keywords: circular economy, machine learning, artificial intelligence

1 INTRODUCTION

The inherent "take - make - waste" of the present linear economy contributes significantly to the resource limits being transgressed. It is undisputed that the necessary transition to a circular economy (CE) is a complex and major challenge, which is why the related transformation processes and instruments are the subject of controversial debate and design. Thus, cities and regions that play a key role as facilitators of the CE urgently need to rethink how the transition process can be accelerated and improved. As part of the overall transition process, innovative approaches in the process assessment, capacity building, financing and regulation are needed to optimize the current linear system, for example through green and clean production techniques, changes in value chain relationships, identification of relevant synergies and cross-sectoral optimization of processes.

Artificial Intelligence (AI) and Machine Learning (ML) can be key enablers of the transition to CE, helping to overcome current challenges and create a much more environmentally sustainable future. It can help to develop durable and sustainable products, drive new circular business models, and support the infrastructure needed to scale the CE [1]. The EU taxonomy [2] provides clear definitions and objectives for environmentally sustainable business activities, but also highly demanding requirements for technical criteria that place AI and ML in a central position in the design of durable and sustainable products and the promotion of new CE approaches.

This article's objective is to provide an overview of the status quo associated with the transition to a CE through AI and ML from several key perspectives. We provide an overview of research articles with AI-based methods in CE, take a closer look at applied methods and algorithms and discuss current areas of application, trends, but also effects and risks of AI applications in CE, such as ethical or data protection breaches. The article is structured as follows. The next chapter provides an insight into the motivation and methodology of this literature study. Chapter three outlines the applications of AI and ML in selected areas of the circular economy. Chapter four discusses algorithmic applications in the circular economy from the perspective of different ML paradigms and methods. Chapter five summarizes the ethical considerations related to the use of AI and ML, and chapter six concludes this literature survey's findings.

2 BACKGROUND AND METHODOLOGY

Since the 1970s, several concepts have been developed to make CE a reality [3]. At that time, awareness of the limited resources and environmental impact of the linear economic model began to emerge, leading to a new way of thinking and new paradigms, such as "Limits to Growth" by [4], which addresses the long-term effects of unlimited economic growth and warns of the limits imposed by natural resources and the environment, "Cradle-to-Cradle" by [5], which emphasizes the creation of products and systems that are designed in such a way that they can be fully recycled or biodegraded at the end of their life cycle without leaving harmful waste, "Performance Economy" by [6], which underscores the importance of maximizing value creation through the use of products and services rather than the mere possession of materials, or John T. Lyle's "regenerative design" model, which promotes the development of products and systems that regenerate natural resources and minimize environmental impact [7]. According to [8], the concept and implementation of the CE was driven by practitioners over the years, such as policy makers, companies, or industry associations, leaving the scientific research to CE unexplored. Given that the global circular economy is on a downward trend - in 2018 the circularity rate was 9.1%, falling to 8.6% in 2020 and 7.2% in 2023 - and that this decline is mainly due to an increase in absolute resource consumption [9], it is obvious how important the scientific contributions in the field of circular economy are and how important it is to narrow the gap between research and practical adoption.

In the present literature survey, the scientific articles listed in the Google Scholar metasearch [10] on the topic of AI and ML in CE were examined. By using 1288 targeted queries incorporating combinations of selected keywords and search operators, we searched for publications that address the implementation of AI and ML in CE, and then consolidated them thematically. Alongside the analyses of selected articles, we also calculate the frequency of selected ML methods and algorithms in all CE-related scientific articles, excluding literature reviews. Based on the frequencies, we calculate trends for selected ML methods and algorithms as the relative difference between Google Scholar entries up to 2023 and entries from 2023. The search operators and keywords were selected, combined, and used explicitly to narrow down the search in the optimal way. Due to the substantial number of peer-reviewed and non-peer-reviewed scientific papers in the database, we see the results obtained as an approximation, but also as a relevant proxy for the status quo of research-relevant ML methods and algorithms in the context of CE.

We identified trends in current CE research for established and emerging ML methods and algorithms. Our survey revealed that the number of scientific articles in the CE domain has significantly increased in the last few years. As the number of research articles increased, so did the number of ML methods and algorithms covered in experimental CE publications. We found that there are 84% more AI and ML affiliated research articles on CE in Google Scholar since 2020, compared to the total number of entries, and 55% more articles since 2023, compared to the respective articles up to 2023.

3 APPLIED MACHINE LEARNING IN THE FIELDS OF CIRCULAR ECONOMY

AI systems aim to replicate human-like cognitive abilities such as thinking, seeing, moving, understanding, generalizing, and learning from previous experiences [11]. In the context of a modern economic system, where there is a constant need for innovative solutions that can improve the overall quality and sustainability of a production or a service while reducing costs, AI technologies can introduce new paradigms [12]. However, CE is attracting increased attention from academics, governments, and businesses, all of whom are becoming increasingly aware of the benefits associated with the integration of AI into CE to enable long-term sustainability. McCarthy [13], defined AI in 1990 as the scientific and technological field concerned with the development of intelligent machines, with a focus on intelligent computer programs. Meanwhile, AI encompasses various paradigms, goals, and methods, including i.a. ML. ML algorithms can be described as a synthesis of mathematical reasoning and error reduction functions [14]. ML models learn from large datasets comprising different data modalities such as structured data, audio, video, or image data and iteratively refine their learning function to minimize errors. Many studies apply traditional algorithms using ML paradigm by training and testing models with independent data or using cross-validation methods for the training and test data to avoid information loss. Such approaches are per se machine resp. statistical learning methods [15]. While for some ML algorithms it is impossible to supervise their training, for most ML algorithms it can be supervised. Typically, such algorithms provide a parameterized output or, e.g., probability values for the inference of the training performance. The objective of supervised algorithms is to achieve the highest possible prediction performance. The performance of ML methods excels when a lot of representative training data is available, which is not always the case in practice. Thus, when the data is sparse, researchers may resort to traditional methods or Bayesian inference [69].

ML has the potential to play a vital role in addressing the critical challenges associated with a smarter CE [16]. By leveraging ML, solutions can be developed to optimize respected areas, enabling more efficient and environmentally friendly practices in the context of the CE. In the CE, some areas have now become apparent that are increasingly using ML methods. Especially within waste and resources management, supply chain management and logistics, renewable energy production, energy optimization, construction and predictive maintenance, ML algorithms are being increasingly used (see examples in Table 1).

In the following, a brief overview of the ML algorithms used in some key areas of CE is given. Given the broad spectrum of CE-related tasks, the area of recycling and waste management encompasses many ML approaches. In addition to the traditional ML algorithms as in [17], where Linear Regression (LR) is used to determine indicators that are suitable for reflecting the environmental impact of waste, or in [18], where the authors use Support Vector Machine (SVM) regressor to optimize municipal solid waste management, many classification or regression problems can also be solved using artificial neural networks (NN) and Deep Learning methods, improving the results for problems where, as in the case of many tasks, the linearity assumption is not justified. Examples of regression problems using NN can be found in [19] for predicting the generation of municipal solid waste or in [20] for predicting the seasonal generation rates of municipal solid waste.

Table 1: Selected recent publications within important CE areas which incorporate ML algorithms. An explanation of the abbreviations can be found in the appendix.

	Authors	Year	Algorithm	ML problem	Reference
Waste managemet	Shahab and Anjum	2022	CNN	classification	[23]
	Kim and Cho	2022	Yolo	object detection	[25]
Recycling	Lopez-Garcia et al.	2022	DT, KNN, Adaboost, MLP	classification	[27]
	Senthilselvi et al.	2020	CNN	classification	[26]
Supply chain & logistics	Liu et al.	2024	SVM	regression	[72]
	Shabanpour et al.	2021	NN	regression	[73]
	Walter et al.	2023	DT, KNN, SVM, MLP, NB	classification	[74]
	Jäämaa and Kaipi	2022	DT, KNN, SVM, RF, AdaBoost, Gradient Boosting	regression	[75]
Renewable energy	Prioux et al.	2022	K-Means	unsupervised	[76]
	Khadke et al.	2023	RF, SVM	regression	[32]
Energy management	Abdelaziz et al.	2024	i.a. K-Means, CNN	unsupervised, classification	[28]
	Eslami et al.	2022	SVM	regression	[31]
Construction	Rakhshan et al.	2021	13 models i.a. RF, KNN, DT, NN, SVM, AdaBoost	classification	[40]
	Shamsabadi et al.	2023	XGBoost	regression	[41]
Predictive maintenance	Rebahi et al.	2023	LSTM	anomaly detection	[45]
	Raghu, et al.	2023	CNN, Transformer	classification	[42]
Manufacturing	Teng et al.	2023	NN	regression	[54]
	Chan et al.	2022	LSTM, CNN	regression	[77]
Product life cycle	Li et al.	2019	NN	classification, regression	[53]
	Sekhar et al.	2023	Gradient Boosting	regression	[52]
CO2 emissions	Wang et al.	2024	LSTM, ridge regression	regression	[61]
	Kanthasamy et al.	2023	SVM, NN, GPR	regression	[48]
Natural resources management	Uddin et al.	2023	NN, SVM, LSBoost, GPR, LR, XGBoost, KNN, RF	regression	[38]
	Long et al.	2022	SVM	regression	[37]
Strategic management	Svanberg et al.	2022	i.a. RF, NN, Gradient Boosting	classification	[78]
	Arranz et al.	2022	OLS, NN	regression	[79]

Applications of different Deep Learning paradigms within waste management include for example the use of transformer-based NN such as Bidirectional Encoder Representations from Transformers (BERT) for the task of text analysis in regard to plastic waste [21] or text analysis in regard to international e-waste policies [22], than the use of Convolutional Neural Networks (CNN) as in [23] where the authors use a CNN to identify and locate areas of illegal dumping, or for example in [24] and [25] for garbage detection using the YOLO Neural Network for object detection and recognition. To improve the process of cell phone recycling, [26] use a CNN model along with feature engineering to increase the amount of training data. In [27], the authors integrate set of classification models, namely Decision Tree (DT), K-Nearest Neighbor (KNN), Adaptive Boosting (Adaboost), Gradient Tree Boosting (GTB), and Multilayer Perceptron (MLP) to setup a system for the selection and optimization of parameters for remanufacturing of recycled fiber. The variety of applications of ML algorithms can also be seen in energy management, optimization, and production. For example, in [28] authors combine self-organizing map networks and CNN for the management of energy consumption in public buildings while [29] apply NN regression in manufacturing to improve energy efficiency through the waste heat utilization. In the area of solar energy, [30] couple the NN model with the Optimization and Machine Learning Toolkit (OMLT) for multi-criteria optimization in the production of photovoltaic solar modules. The authors in [31] use Support Vector Regression (SVR) for the planning and use of a district heating system with solar energy and heat pumps while [32] address the problem of weather unpredictability in solar power generation by applying LR, Random Forest (RF) and SVR based on weather and system inverter data. In the field of bioenergy production, a multitask model [33] is used along with NN regression, RF and SVR for hydrochar property prediction, noting the best performance for Deep Neural Networks (DNN) and in [34] the authors use NN regression together with RF and Elastic Net for biogas production analysis. In relation to the sustainable optimization of the hydrothermal liquefaction process, [35] apply RF to classify biomass data while in [36], the authors use Gradient Boosting Regression (GBR) and RF regression for the prediction and optimization of bio-oil production from hydrothermal liquefaction of algae. Regarding analysis of algae cultivation for the use of renewable fuels, [37] use a model based on SVR. In the field of natural resource analysis, examples of the application of ML can be found in [38] for the development of optimization techniques to improve the water quality, where the authors use eXtreme Gradient Boosting (XGBoost) model or in [39] using multiple regression to predict the extent of glacier melt.

In the construction sector, [40] developed a probabilistic prediction model that combines the sampling method with a RF estimator to predict the economic reusability of construction elements while [41] apply XGBoost for the green concrete mix optimization by identifying mixes with better environmental properties and low production costs. In [42], authors apply a multi-label classification task for material recognition of building facades using GIS (Geographical Information Systems) data and street views and set up three image classification models, namely Vision Transformer, Swin Transformer V2 and ConvNeXt. Regarding image-based inspection and monitoring of buildings, [43] combine binary thresholding of images with a DT to detect cracks in concrete surfaces, map the results to the Building Information Modeling (BIM) model, to update and visualize the current building state. [44] attempt to estimate construction waste generation using multiple linear regression, DT, Gray Model and NN with study area focusing on the Greater Bay Area in China, one of the world's most dynamic regions in terms of construction activity. In the field of predictive maintenance, [45] proposes an ML based maintenance for enabling the extension of the life cycle of machines and appliances using a DNN along with Long Short-Term Memory neural network (LSTM). In view of the importance of reusing machines up to their maximum lifetime, [46] set up a predictive maintenance system by training a Siamese NN in which the pre-trained model is fine-tuned. Other articles that use ML in the context of CE are [52], who apply a GBR to predict the remaining useful life of batteries, and [53], who apply a multi-criteria procedure with a NN to assess the remaining useful life of end-of-life products. Another interesting approach in sustainable chemical production using NN regression is provided by [54].

Studies within the framework of CE use ML methods to investigate the effects on the concentration of greenhouse gases. For example, based on experiments with Gradient Boosting Decision Tree (GBDT). [47] show the extent to which biochar produced from food waste is an effective CO2 adsorbent. In [48], the authors investigate similar problem using SVM, Gaussian Process Regression (GPR) and NN, which showed superior performance. In relation to CO2 emissions, [49] apply optimized NN model to estimate the time of reaching carbon peak and carbon neutrality in China. Using Deep Time Series Forecasting method [50] employ the Bidirectional Long Short-Term Memory Neural Network (BiLSTM) to estimate the environmental change in carbon emission patterns in South Asia and conclude that CO2 emissions will reach by 2030 about twice the amount emitted today. Also, [51] use an LSTM model along with Ridge Regression to calculate Shanghai's carbon emissions based on three policy scenarios, considering a differentiated energy structure and emission reduction technologies.

The articles examined above show the variety of applications of ML algorithms in CE in recent years. Furthermore, it can be observed that studies combine or compare the performance of multiple algorithms for the problem at hand. The following section takes a closer look at the consideration of different ML paradigms and methods in CE research.

4 THE KEY PRADIGMS, METHODS AND ALGORITHMS OF MACHINE LEARNING IN THE CIRCULAR ECONOMY

In the following we discuss a subset of the complex ML taxonomy, considering the methods that have a research relevance within CE. We provide an overview of the methods that are incorporated into surveyed scientific contributions and which, based on [55][56], are in the field of ML of major importance and exhibit a growing trend recently. Consequently, the following ML sub-areas are examined, namely analysis of specific data modalities such as text and visual information (Natural Language Processing - NLP, Computer Vision), analysis of multiple data modalities (Multimodal Learning), analysis of multiple ML tasks (Multi-Task Learning), analysis incorporating combinations of algorithms (Ensemble Learning), collaborative ML (Federated Learning), strategy ML (Deep Reinforcement Learning), as well as Deep Time Series Forecasting and Deep Unsupervised Learning.

Figure 1 shows the popularity trends of these ML methods covered in experimental studies within CE from 2023. The trends shown reflect the relative occurrences in the experimental CE publications obtained using selected keywords and search operators. Although the number of absolute keyword entries for Federated, Multimodal, Deep Unsupervised and Multi-task Learning is low in comparison, suggesting that these methods are still in an experimental phase within CE, the relative comparison of the entries before and after 2023 from the Figure 1 shows a clear trend for the first three ML methods. Ensemble and Reinforcement Learning are enjoying increasing popularity [70] and are also on the rise in CE in accordance with the trends observed. According to the absolute number of keyword entries on the Google Scholar the most used Deep Learning methods in CE are Computer Vision, Deep Time Series Forecasting and NLP. Computer Vision is at the forefront, especially because of the versatile applications of CNNs as well as object recognition and segmentation NN. However, none of these three methods are experiencing a notable trend in research to CE since 2023.

All these methods offer high potential for obtaining accurate results and are occasionally combined in the research design with each other or with other techniques. For example, [57] propose an approach in which they combine Blockchains and Federated Learning to optimize recycling processes, extend the life of electronic devices, and improve e-waste management.

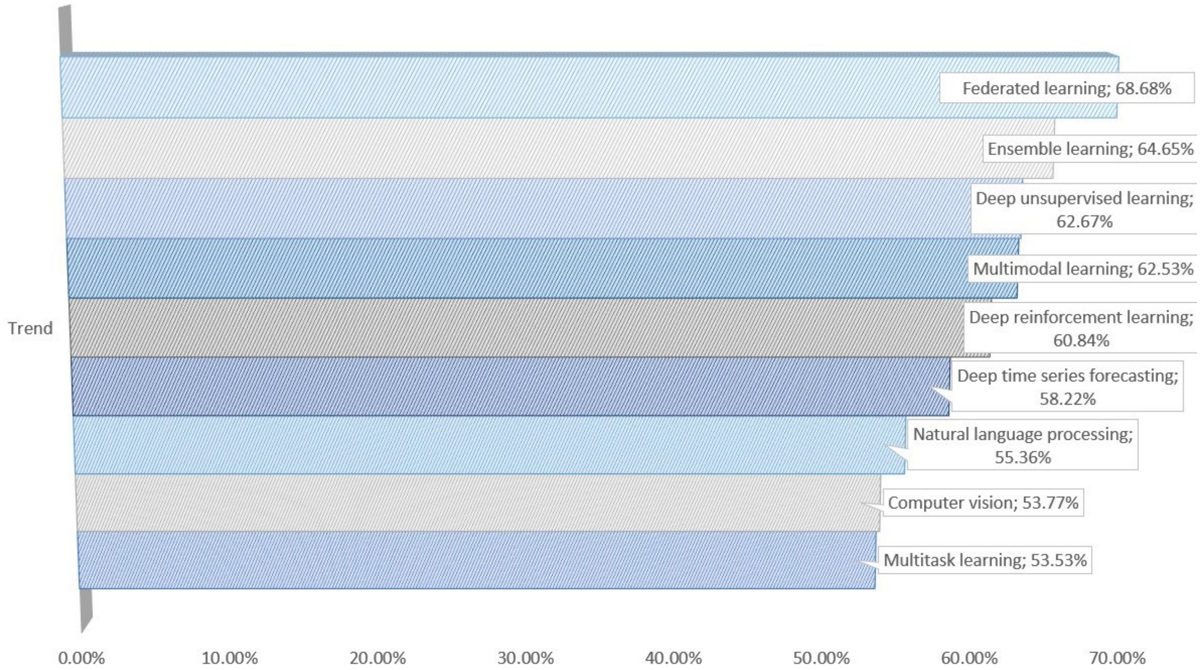

Fig. 1: Current trends (in %) of selected ML methods in experimental CE studies based on estimated differences in keyword entries up to 2023 and from 2023 onwards.

For sorting COVID-related medical waste, [58] apply Ensemble Learning using image and text features along with multiple feature extraction methods and train four classifiers (K-NN, 2 x SVM, ANN) to obtain the result by majority voting. In [59] the authors apply Ensemble Learning to predict the energy consumption of aircraft parts regarding green manufacturing. Combining the paradigms of Reinforcement Learning with Computer Vision in the field of waste management is attracting increasing interest in research as in [60] but also in the field of energy management as in [61] where the authors combine both to improve the fuel consumption by autonomously learning the optimal control strategy from visual inputs.

Alongside Supervised Learning and Unsupervised Learning, Reinforcement Learning is one of the fundamental paradigms of machine learning. Reinforcement Learning algorithms try to find the optimal way (strategy) to achieve a specific objective or improve performance on a specific task. This is based on the paradigm of reward and punishment algorithmic mechanism, which is important in robotics, NLP, or automotive driving. The algorithms can be used in versatile ways and can be combined in practice with other ML methods, such as Computer Vision algorithms for example in the field of waste management for automatic recycling. Automated, AI-supported waste recycling systems such as those developed by [62] are used for construction waste recycling and, for some years now, also within municipal waste management. Such systems incorporate robots that can recognize and sort waste fractions of different shapes, weights, and sizes. The robots are trained for Computer Vision and Reinforcement Learning tasks based on sensor fusion [60].

Meanwhile, Reinforcement Learning incorporates various algorithms, some of which are unique programmatic paradigms, and the others are the further development of established Reinforcement Learning algorithms, such as: A2C, A3C, Soft AC algorithms based on the actor-critic paradigm or Proximal Policy Optimization (PPO), or Trust Region Policy Optimization (TRPO) algorithms based on policy optimization. The occurrence of Reinforcement Learning methods in CE-related scientific publications is still low compared to NLP and Computer Vision, but there is a clear upward trend from 2023, as can be seen in Figures 1 and 2. To date, A2C and Deep Q-Learning have been the most widely used in CE, with the latter currently showing the largest trend compared to other reinforcement learning algorithms.

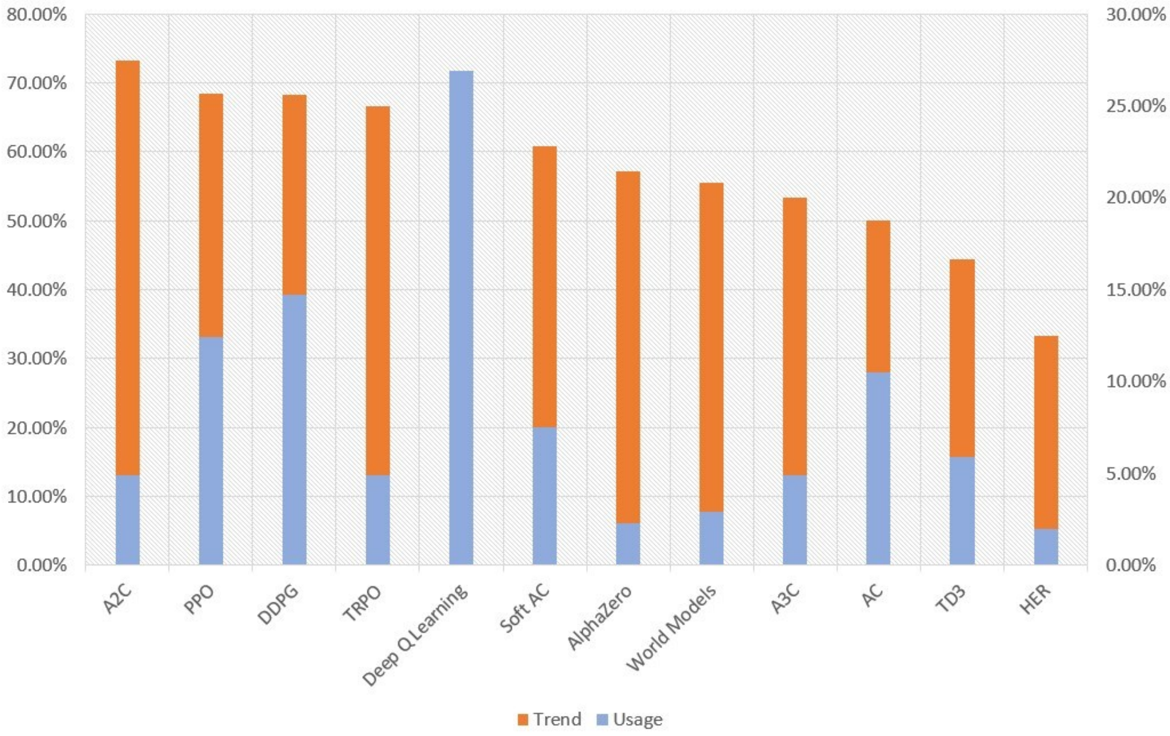

Fig. 2: Approximate usage of Reinforcement Learning algorithms in experimental CE studies in % (from 2020) and trends since 2023. Explanations of the abbreviations on the x-axis in the illustration: Actor-Critic based Algorithms - AC, A2C, A3C, Soft AC | Policy optimization-based algorithms - Proximal policy optimization (PPO), Trust Region Policy Optimization (TRPO) | Deep Deterministic Policy Gradient (DDPG), Twin Delayed DDPG (TD3) | AlphaZero is generic algorithm based on Deep Learning, RL, Monte Carlo tree search, and self-play technique | Deep Q-Learning incorporates a DNN | World Models stands for RL models trained in complex environments | HER stands for Hindsight Experience Replay algorithm.

Unsupervised Learning is a rapidly advancing area of ML and recently Deep Unsupervised Learning has been attracting increasing interest from researchers, including those in CE. The basic paradigm is capturing rich patterns in raw data with DNN in a label-free manner, emulating raw data distributions or working on "puzzle" tasks that require semantic understanding in a Self-Supervised Learning manner. Deep Unsupervised Learning offers numerous applications, such as the generation of novel data, conditional synthesis of data modalities, data compression or the improvement of downstream tasks in the context of Transfer Learning. Many Deep Unsupervised Learning methods are still very experimental, but models such as for image generation (conditional GANs), language modeling or self-supervised models such as Contrastive Predictive Coding (CPC) already demonstrate remarkable performance, while on the other side Autoregressive models, or Unsupervised Learning approaches for Reinforcement Learning still have room for improvement [71].

RNN-based networks are often used in time series analysis. These time series models are suitable for sequential data of different lengths for signal processing, text analysis or anomaly detection. However, as can be seen in Figure 3, along with RNN, the long short-term memory (LSTM) network, a special form of RNN, is the most used algorithm for time series problems within CE (see works in [45,61,77]). LSTMs also exhibit the most pronounced trend among all investigated time series models. Another form of LSTM is the bidirectional LSTM, which learns bidirectional dependencies between time steps, which is also applied in [21]. Other trending time series algorithms in the field of CE are encoder-decoder based Transformer Networks, Prophet Algorithm from Facebook Research [80], Graph NN and Grey Model. We noticed that traditional linear discrete time series models such as ARIMA have also been used often in CE, but compared to deep learning models, they receive less attention in current research.

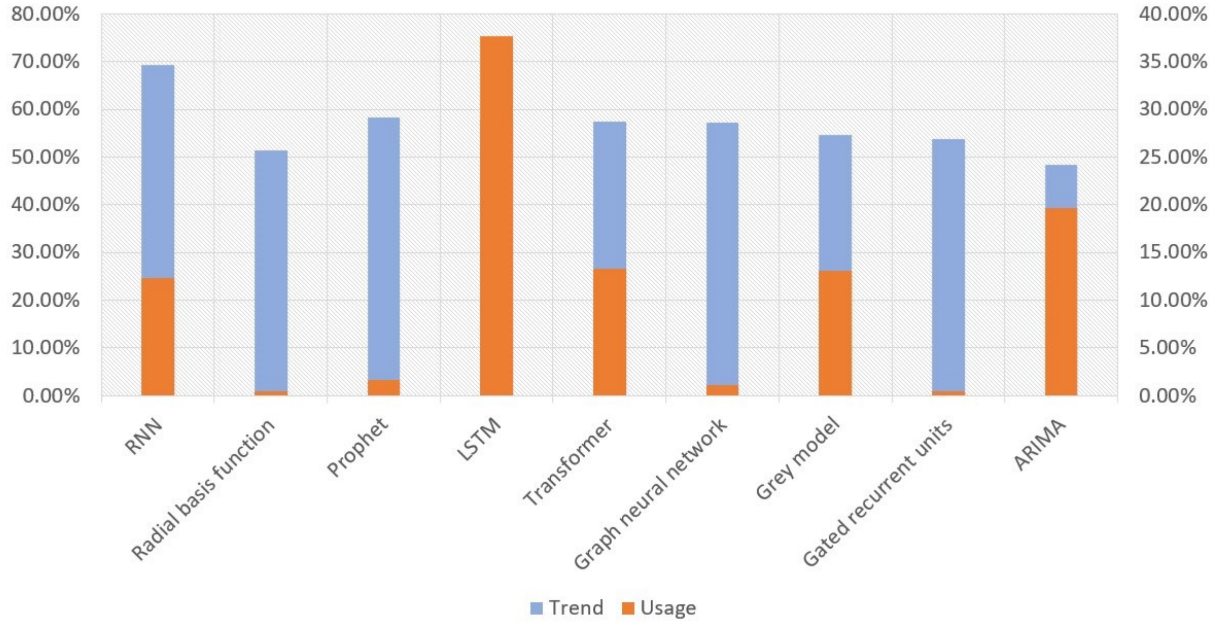

Fig. 3: Approximate usage of time series algorithms in experimental CE studies in % (from 2020) and trends since 2023. Recurrent Neural Network Long Short-Term Memory (LSTM) exhibits both the most use and the most emerging trend among traditional and Deep Learning Time Series Forecasting algorithms in CE publications.

The summary in Chapter 3 shows that many tasks in the field of CE are regression-based tasks that incorporate variety of algorithms. As part of the Supervised Learning paradigm, classification and regression play an essential role in algorithmic problem solving within CE. Just as with the regression-based problems in CE, both Deep Learning and traditional algorithms applied by means of the ML paradigm are used for classification problems. In addition, the scope of application of the classification algorithms may be just as large, also because the Deep Learning area more often deals with classification problems, especially in the field of Computer Vision where CNNs are most used. Some typical examples of the use of CNNs can be found in waste management, recycling, and material analysis.

Figure 4 shows the tree map based on the absolute keyword entries for the classification algorithms in the CE research. The numbers refer to experimental studies, excluding literature reviews or surveys. To this end, we explicitly excluded the algorithms shown in Figure 4, which are used for regression-based tasks, using systematic online queries. We do not analyze Deep Learning-based algorithms because of the many NN types in Computer Vision. It can be seen from Figure 4 that Random Forest, Decision Tree, and Support Vector Machine are the most popular classifiers in the CE domain. They are followed by K-Nearest-Neighbor, Multi-Layer Perceptron and Logistic Regression. Softmax Regression (Multinomial Logistic Regression) and Boltzmann Machine-based classifiers are mentioned the least in the publications. Based on the posed comparisons, a clear picture can be inferred of the extent to which certain classifier algorithms are anchored in the domain of CE.

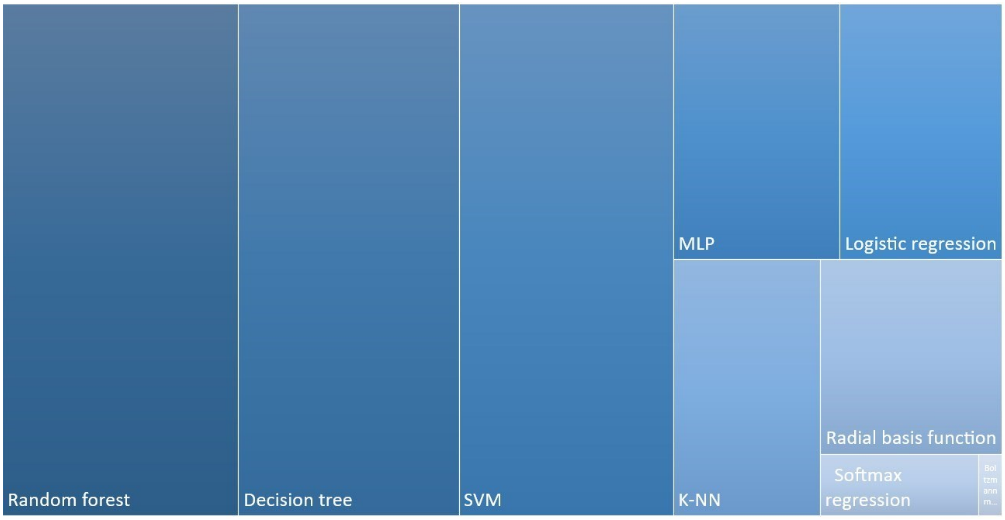

Fig. 4: Tree map for approximate usage of ML classifiers within experimental CE studies as of 2020. From the figure it can be noticed that Ensemble Learning method Random Forest (which incorporates a multitude of Decision Trees) is the most used classifier in the CE domain.

5 IMPLICATIONS AND RISKS OF AI AND ML DEPLOYMENT WITHIN CIRCULAR ECONOMY

The use of AI in the development of products and businesses offers many potential benefits. However, without proper consideration of the associated risks, the use of AI could undermine its benefits by being harmful and potentially disfavored by society [63]. The circular economy depends on partnerships and collaborative processes between different actors. Given the interconnectedness of supply chains, a single economic actor cannot close the chain exclusively, which implies that circular economies are impossible without respective collaboration. Data forms the basis for these intra- and interorganizational links as it provides stakeholders with information on the various parameters of the underlying factors such as location, quality, and availability. However, data handling may also harbor risks for data protection. In terms of data collection, the proliferation of tracking and measuring devices, such as IoT (Internet of Things) in the personal domain, is in many cases a prerequisite for AI-powered CE products. This poses a significant risk for privacy breach [64]. In addition, [65] points out the ethical implications as the increased data collection could also jeopardize consumer privacy.

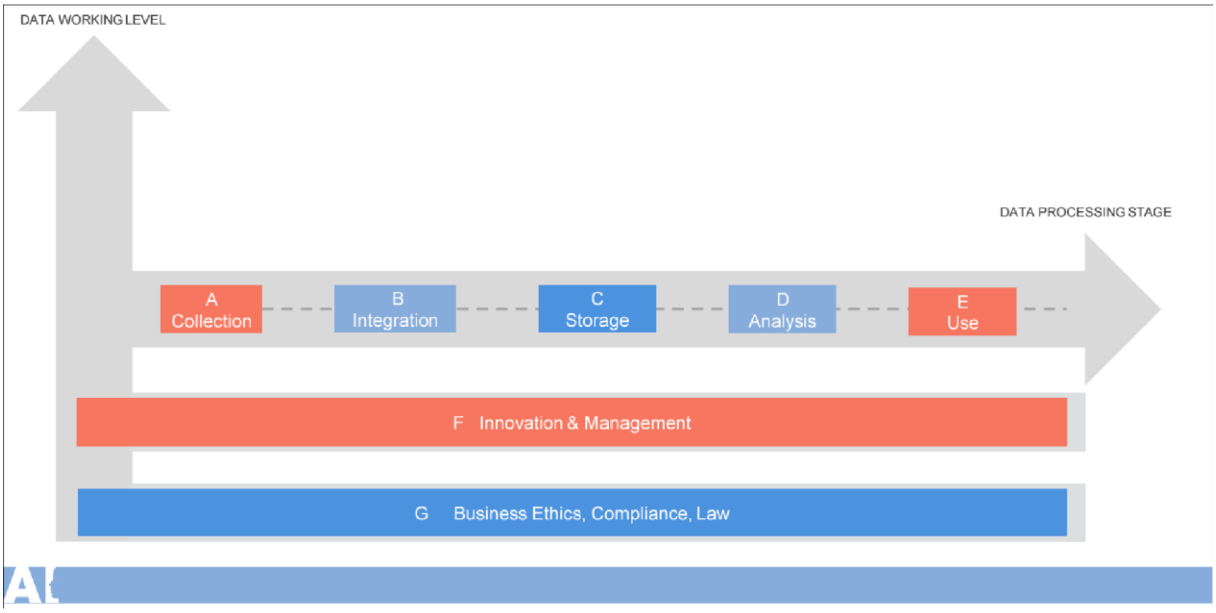

Fig. 5: Typical example of the data value chain in companies. Maintaining the outlined orthogonal relationship between business compliance, ethics and law and the data processing is essential for proper data use and sharing.

Another issue is how organizations should share related data in a meaningful way while protecting privacy. In terms of data sharing and exchange, the boundary between proprietary, private, and open data in the CE processes may often be fuzzy. Thus, both the ethical data value chain inside companies as depicted in Figure 5 and between companies is important for the implementation of CE objectives.

In the existing literature, the adoption of algorithm-based business models such as automated dynamic pricing and matching is regarded positively. AI can be employed to scale circular business operations by automatically setting prices for reused products and matching them with potential consumers, based on parameters such as market demand, product conditions, or consumer profiles. However, the implementation of automatic dynamic pricing and algorithmic profiling has encountered challenges, leading sometimes to unfair or potentially discriminatory outcomes [63,66,67,68]. Automated dynamic pricing and algorithmic profiling based on companies' criteria can lead to unfair or discriminatory outcomes. However, [67] argues that some algorithmic biases are justified in certain cases, such as when the product or service collides with constraints what incurs higher costs. [65] formulates that individual pricing and advertising of circular economy products containing a component that correlates with certain features could unintentionally lead to discrimination.

CONCLUSION

This literature survey has shown that the number of scientific publications regarding the application of AI and ML within CE has increased significantly in recent years. We could identify several emerging ML methods and algorithms that are used in a variety of CE areas. In summary, for all ML algorithms considered in this study, we found that since 2020 there are 84% more AI and ML related experimental articles in CE within the Google Scholar records compared to relate all time Google Scholar records. Since 2023, there have been 55% more articles compared to all articles until the year 2023. As mentioned above, these results are an approximate estimate, but they can serve as a useful proxy to reflect current trends in CE regarding the application of AI and ML.

AI's potential to replicate human-like cognitive abilities, its successful application in various industries and the increasing availability of data today make it a valuable tool for achieving the objectives of the CE as well. By supporting the design, development and maintenance of circular products, AI can serve as an accelerator to facilitate the implementation of the 3R principles (Reduce, Reuse, Recycle) and thus the development of environmentally friendly designs. The scientific literature shows that AI and ML are increasingly seen as highly useful tools for generating initial design concepts, adapting existing processes based on environmental parameters and contributing to the development of sustainable materials. Such methods play a crucial role in analyzing product performance over time and provide valuable insights for improvements, thereby extending the life of products.

We have also deliberately drawn attention to the risks of data handling and data exchange and the potential for AI-based solutions to lead to unfair outcomes through incorrect design, deployment, or practices. Awareness of these challenges is crucial to ensure that AI-supported circular business processes remain fair and that harmful and discriminatory practices are avoided. A balance between the use of data and the protection of privacy is essential for the successful and ethically responsible implementation of CE.

Overall, it is evident from the results that the use of AI and ML in CE is on the rise. The potential of using valuable AI and ML tools and techniques to optimize CE products and processes is becoming increasingly recognized.

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APPENDIX

Table 2: Definitions of the algorithm abbreviations

LR	Linear Regression
SVM	Support Vector Machine
NN	neural networks
BERT	Bidirectional Encoder Representations from Transformers
CNN	Convolutional Neural Networks
DT	Decision Tree
KNN	K-Nearest-Neighbor
Adaboost	Adaptive Boosting
GTB	Gradient Tree Boosting
MLP	Multilayer Perceptron
OMLT	Optimization and Machine Learning Toolkit
SVR	Support Vector Regression
RF	Random Forest
DNN	Deep Neural Networks
GBR	Gradient Boosting Regression
XGBoost	eXtreme Gradient Boosting
BIM	Building Information Modeling
LSTM	Long Short-Term Memory
GBDT	Gradient Boosting Decision Tree
GPR	Gaussian Process Regression
BiLSTM	Bidirectional Long Short-Term Memory Neural Network
NLP	Natural Language Processing
PPO	Proximal Policy Optimization
TRPO	Trust Region Policy Optimization
DDPG	Deep Deterministic Policy Gradient
TD3	Twin Delayed DDPG
AC	Actor Critic
A2C	Advantage Actor Critic
A3C	Asynchronous Advantage Actor-Critic
Soft AC	Soft Actor Critic
conditional GAN	Conditional Generative Adversarial Network
CPC	Contrastive Predictive Coding