# Role of Artificial Intelligence in Circular Manufacturing: A Systematic Literature Review

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**Abstract:** Circular Economy (CE) empowers firms (micro-level), network of firms (meso-level), cities, regions and nations (macro-level) sustainability. CE potentialities in making regenerate resources are even greater if supported by technologies, and Artificial Intelligence (AI) is gaining momentum in this regard. The extant literature presents a limited investigation of the exploitable synergies among CE and AI at the different scales of CE adoption in manufacturing, also named Circular Manufacturing (CM). Indeed, this paper entails a systematic literature review to investigate the state-of-the-art in this domain proposing future research opportunities. Among the findings, AI exploitation is advanced at micro-level, whilst the meso-level, macro-level, and the synergies among the three levels require further exploration.

*Keywords:* Circular Economy, Circular Manufacturing, Artificial Intelligence, Manufacturing, Sustainability, Literature Review

## 1. INTRODUCTION

Circular Economy (CE) is covering a prominent position in boosting sustainable development, being it an industrial economy purposely designed to recirculate resources by shaping regenerative systems (The Ellen MacArthur Foundation, 2012). It is based on the values of slowing, narrowing and closing resources loops (Bocken et al., 2016), that can be embraced mainly at three scales of adoption, thus at the macro level (e.g. nations, regions and cities), meso level (e.g. networks of firms) and micro level (e.g. firm, product) (Ghisellini et al., 2016). This economic model is attracting the attention of scholars that studied how CE is adopted in manufacturing, being it considered one of the most resource-intensive sectors. Within manufacturing, CE values can be operationalized into different strategies such as remanufacture, recycle, industrial symbiosis, etc. which concurrent adoption takes the name of Circular Manufacturing (CM) (Acerbi and Taisch, 2020). Industry 4.0 (I4.0) technologies represent a great opportunity to pursue the transition towards a circular system by promoting the exploitation of data gathered for sustainable aims, especially concerning the manufacturing sector (Nascimento et al., 2019). Out of all the I4.0 technologies, Artificial Intelligence (AI) is prominently positioned to drive CE values embracement (The Ellen MacArthur Foundation, 2019). Indeed, AI enables using appropriately data gathered from industrial systems (Mihailiasa and Avasilcai, 2019) thanks to the capability of AI to track and monitor process and product data (Malahat Ghoreishi and Happonen Ari, 2019). Considering the great potentialities of exploiting AI to embrace CE values in manufacturing, even at different scales of adoption (i.e. micro, meso, macro), the present contribution aims at retracing extant scientific literature to depict the state-of-the-art (SOTA) thus answering to the following research question: "*How does AI support CM at the different scales of adoption at the state of the art of the scientific literature?*". Therefore, the research objective (RO) is to investigate the SOTA about how AI could support the implementation of CM strategies at micro, meso, and macro levels opening the way for future research directions.

The paper has the following structure. Section 2 describes the research methodology used, section 3 elucidates the results obtained based on the theoretical framework developed by the authors, in section 4 the results are discussed, and section 5 outlines the conclusions and the research agenda.

## 2. RESEARCH METHODOLOGY

A systematic literature review (SLR) has been performed to span the extant scientific knowledge in a structured and systematic way relying on predefined criteria to address the RO by selecting the eligible contributions for the review. As the scope of this review lies in the industrial domain, Scopus was chosen as scientific database, and it was queried as follows: TITLE-ABS-KEY (("Circular Economy" OR "Circular Manufacturing") AND "Artificial Intelligence"). Since the term "circular economy" is the most diffused one, it has been added as keyword to ensure gathering all papers of interest. Then, to assure compliance with the research scope, only those papers referring to manufacturing have been selected during the screening process. Instead, considering that AI represents a specific topic within I4.0 domain already diffused in the literature, only the keyword "artificial intelligence" has been used. The search process was stopped in July 2020. No timeframe constraints were adopted to include both the most recent documents and seminal papers, and only English documents were included. As an outcome, 50 documents were firstly identified, out of which only 29 were considered eligible for the review. The selection process was performed into two subsequent phases (see Fig. 1): 1st screening reading the title and the abstract, 2nd screening by reading the entire contribution. As a result, 42% of the discarded papers were eliminated since they did not explore the adoption of AI as support tool to implement CM strategies. A further 33% was eliminated since there was not a direct link to CM but rather to sustainability in general, and for the 25% it was not possible to perform the integral reading of the paper.

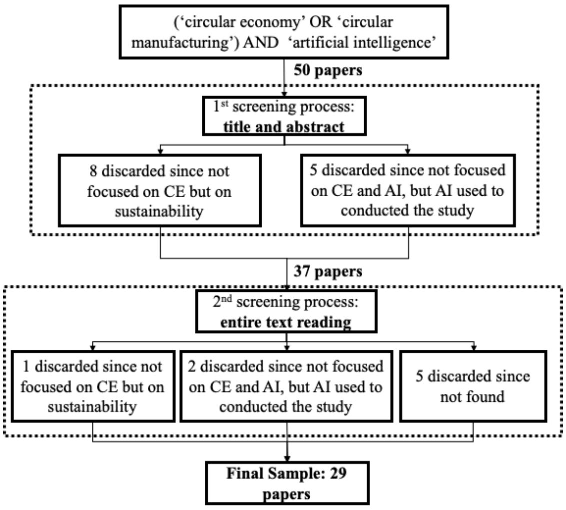


Fig. 1. Selection process of eligible papers for the review

In section 3.1., a statistical analysis has been conducted on the eligible contributions, to investigate the researchers' interests, by evaluating (i) the distribution of the contributions over the past years, (ii) the CM strategy tackled in the contribution (i.e. reuse, remanufacture, recycle, waste management, resource efficiency, cleaner production, industrial symbiosis, closed-loop supply chain, servitization and circular design (Acerbi and Taisch, 2020)), and the scale of adoption (i.e. micro, meso macro). In section 3.2., the sample of eligible papers has been analysed based on the framework, developed by the authors, reported in Fig. 2.

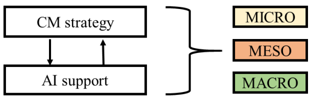


Fig. 2. Theoretical framework to explore AI-CM synergies

It has been investigated how the adoption of different CM strategies is supported by AI throughout the different scales of adoption (i.e. micro, meso and macro (Ghisellini et al., 2016)) to expand the firm perspective towards the entire ecosystem. This analysis enabled to investigate the SOTA about the current status of the adoption of AI for CM not only at firm level but also at network of firms and nations levels, enabling to detect future research directions to be addressed.

## 3. LITERATURE REVIEW RESULTS

### 3.1. Descriptive Statistics

The first identified paper dates to 2010 with the publication of a single contribution, while most of the papers (i.e. 83%) have been published starting from 2018, highlighting a growing research interest in AI for CM. In addition, the year 2010 coincides with the years around which started to be the diffusion of CE in manufacturing and Industry 4.0 paradigm.

To dig deeper into understanding how scholars are tackling the concurrent analysis of CM and AI in the extant literature, each contribution has been mapped according to the CM strategy addressed and the scale of adoption investigated (see Fig. 3). The contributions might cover more than one strategy per time leading to a total value greater than 29.

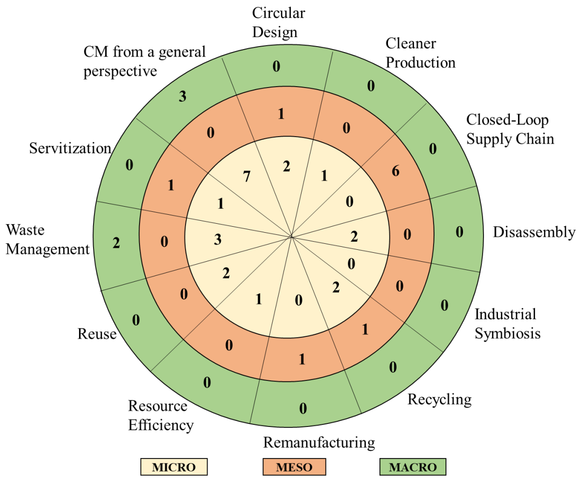


Fig. 3. AI exploitation in CM strategies adoption at micro, meso, and macro levels

As visible from Fig. 3, most of the contributions tackles with the micro level. Lots of researches are focused on CM in general without looking at a specific strategy obtainable benefits. In addition, large interest is shown around the waste management strategy which remains also the most diffused one at the macro level. At meso level instead, there is a heightened interest in using AI to facilitate closed-loop supply chain adoption while industrial symbiosis is neglected if considering the publications identified for this review. Looking at Fig. 3, the number "0" is quite diffused; whereas it is normal if considering the "0" publications regarding closed-loop supply chain and industrial symbiosis at micro level, it is interesting to see a "0" for the remanufacturing strategy at micro level and to see limited attention at macro level in general. These results underline the still limited but growing investigation of AI in CM, that is also emphasised by the scarce number of publications identified while performing the review.

### 3.2. Contributions Analysis

AI is gaining momentum in supporting the adoption of CM strategies, in enhancing energy efficiency, and enabling the extension of product and components useful life, by grasping as much as value possible from resources (Cioffi et al., 2020). At factory level (i.e. product and process), AI boosts the scaling up of CE values by supporting the decision process through the real-time tracking and monitoring of products, intending to evaluate their residual value (Mboli et al., 2020). AI can support the transformation challenges too, by integrating knowledge into operative aspects in a safe and quick way (Drabble and Schattenberg, 2016), enhancing system flexibility (Wang, 2011). In addition, AI can be used to promote the introduction of visual tools that provide a clear vision over the information flows regarding products, resources and processes, and facilitate the investigation of the unexplored benefits gained by CE embracement (Bianchini et al., 2019). Moving the focus to the macro level, with the monitoring of CM strategies adoption, AI stimulates the resource reutilisation in one specific city (Runaghan, 2019).

As visible from Fig. 3, scholars extensively investigated how AI can support closed-loop supply chain adoption. Indeed, AI could highly stimulate the transition towards circular systems by involving all supply chain actors, thanks to the gathering of real-time information on resource consumption and waste. This enables to efficiently analyse the current situation and adapt the system according to the environment (Rajput and Singh, 2019). Actually, the transition towards this new paradigm has impacted different aspects of companies, among which their interactions and logistics. The latter two, at supply chain level, have required advanced technological integration and a cultural change of people involved, which can be addressed through an adequate training conducted relying on AI (Zijm and Klumpp, 2015). In addition, the adoption of closed-loop supply chain requires overcoming some barriers, and AI could efficiently face them by managing data related to returned products. Indeed, a huge problem regards the uncertainties about the quality, quantity and time of returned products. AI can be used to develop decision support tools to determine the quality of a product, the needed reprocessing activities, and in case no regenerative processes can be implemented, AI supports the identification of the most appropriate and cost efficient disposal modes for the different returned products (Lechner and Reimann, 2019). Decision support tools relying on AI are also introduced for the management of spare parts in automotive sector (Makarova et al., 2018). Indeed, AI highly supports also waste management strategy adoption especially regarding the management of municipal waste produced by the end users. For instance, AI has been adopted through smart bins that have sensors embedded allowing to analyse waste-related data detecting the materials within waste to ease its management (Sarc et al., 2019). AI has been used as well to improve the e-waste efficiency via smartphones to manage municipal waste by optimising the loading and the packing of waste on vehicles (Nowakowski et al., 2020). Web-based solutions have been developed to support the decision process along the supply chain of municipal solid waste by tracking waste quality, waste quantity and their related time variability to create market opportunities having tracked also the waste contractors (Paul and Bussemaker, 2020). In addition, the adoption of AI has been also used to support the decision making process in waste management for wastewater treatments (K. Jaderko, 2018) and for bio-waste treatments, to develop bio energy by relying on criteria which cover the social, environmental, and economic aspects (Vlachokostas et al., 2020) with the final goal to reuse waste as a resource. Actually, an opportunity to reduce waste generated by end-users is represented by the implementation at company level of new circular design strategies which, to be effective, must be also linked to an adequate network. For instance, Niu et al. 2019 proposed the adoption of AI to support the development of a model which enables to take investments decisions, regarding the design for remanufacturing of products, according to the dynamics of the supply chain by boosting either vertical or horizontal cooperation (Niu et al., 2019). Through that research, Niu et al., (2019) enabled to extend the traditional micro-level vision of circular design strategy to the meso level, requiring the interaction among parties. In addition, to enhance the potentials of circular design within a network, another usage of AI has been seen in the creation of an algorithm used, for instance, to map the vehicles, adopted to collect waste for recycling, to balance their loading and better manage their scheduling (Xiaonan Zhang et al., 2011). Indeed, as widely acknowledged, decisions taken at design stage are largely linked with the adoption of the other CM strategies and, AI introduced during the design stage enhances the product circularity characteristics by enabling to increase resources traceability and to optimize the testing phase (Malahat Ghoreishi and Happonen Ari, 2019). On one hand, manufacturers, thanks to the introduction of sensors embedded into products, and the capability of AI to manage a complex set of data, can control product performances along their entire lifecycle and optimize them in real time or for the future design initiatives to guarantee better and optimised performances in future product releases. On the other hand, AI represents an opportunity to create different versions of product prototype without wasting resources but ensuring the alignment with market needs (Malahat Ghoreishi and Happonen Ari, 2019). AI has the potential, thanks to the possibility to exploit complex data, in managing also the material acquisition process. Then, once the product has been sold to end user, data mining and analytics boost the introduction of servitization strategies and promote resource recycling and reuse, thanks to the interaction among different stakeholders along the supply chain (Su et al., 2019). The possibility to disassemble, recycle, remanufacture or reuse a product depends on product characteristics which have been defined at design stage. Starting from the possibility to disassemble a product, product design becomes essential to be implemented under a circular perspective and it is facilitated by decision support tools to promote a modular design (Stavropoulos et al., 2020). In addition, the disassembly becomes more efficient if automatized, that can be done via the adoption of collaborative robots that are boosted by AI (Poschmann et al., 2020). Once the product has been disassembled, the product components can be recycled and to do that, by ensuring a cost efficient solution, a data intelligent algorithm has been proposed. This algorithm works based on the information embedded in used parts characterising the component and thus, it enables to facilitate the decision process by creating a prediction model of used parts (Fan and Cai, 2019). CM transition is also underpinned by appropriate manufacturing processes, reflected in cleaner production and resource efficiency, whose adoption can be facilitated as well by AI according to the extant literature. AI covers a promising position in contributing to processes optimisation by reducing resources usage and increase sustainable performances. Indeed, cleaner production, relying on AI for the development of decision-making tools based on data analytics, pushes towards energy, water and utilities usage reduction (Fan et al., 2020).

## 4. DISCUSSION

In the extant literature, AI arose to be a great opportunity in enabling product and process based circularity since it ensures the treatability and management along the entire product lifecycle. Using complex data, interventions can take place starting from the material acquisition until resource disposal or resource introduction in a new lifecycle. AI seems to register great potential for enabling the adoption of most of CM strategies and at different scale levels. Therefore, thanks to the specific features of AI representative technologies, all working with similar cognitive human characteristics of learning and reasoning, AI has great potentialities to be exploited to pursue the transition towards CM.

Starting from the micro level, (i.e. firm level thus, product and process), it is possible to envisage the potential of tracking in real-time huge amount of complex data which enable to support the decision-making process in pursuing the right path relying of the contextual situation. In addition, AI can be exploited to manage waste coming from the usage of the product by end-users by recognising the materials embedded into products and to decide how to recycle or dispose them. Therefore, concerning the product side, different opportunities arose regarding the possibility to use AI to map data coming from the product usage by end-users and to propose adequate services customised on consumers' behaviours and needs. Concerning processes, AI enables to keep high sustainable levels along the production processes whenever cleaner production or resource efficiency strategies are applied. More specifically, thanks to tracking capabilities, AI could be used for the development of decision-support tools which enable to evaluate the best path according to the energy, water and other utilities usage during the production process. AI, exploited via collaborative robots, makes automated the disassembling tasks which are necessary to easily recycle the product materials or to re-manufacture products. More precisely in these cases, AI allows the exploitation of the potential of data analytics to evaluate product residual value, so to estimate its possible reuse, or to evaluate the best remanufacturing path option at the end of its lifecycle. Finally, AI is also applied to reduce waste generated during the prototyping phase.

In line with the great benefits highlighted for firms, AI also represents a great opportunity at meso-level in supporting collaboration among entities building on reliable data. Indeed, whenever a product is moved along the supply chain, it can be tracked and monitored, and data regarding specific waste can be analysed as well to evaluate the residual value of resources, so to successfully give them new life. For instance, AI features increase the ease of tracking of quantity, quality and time data of returned products, enabling to face barriers for adequate closed-loop supply chain management. However, limited attention is given to AI adoption supporting Industrial Symbiosis, enabling the evaluation of the links among industrial entities to exchange waste as resources.

The macro level sees benefits from the usage of AI as more complex data are required to be managed and for which AI is envisioned to be a great asset. For example, AI provides the opportunity to monitor and appropriately manage the waste generated by municipalities and this indirectly can benefit the industries circularity if stronger relationships would be established among firms and policymakers.

To conclude, this review enabled to elucidate the benefits emerged in supporting the implementation of CM strategies with AI. A summary is reported in Table 1.

**Table 1. AI benefits in CM adoption at different scales of adoption**

| *Scale* | *Entity impacted* | *CM strategy* | *AI benefits* |
|---|---|---|---|
| Micro | Product | Circular Design | Tracking the material starting from the acquisition phase.<br>Prototyping the new product without wasting resources during the test phase<br>Keeping high product modularity exploiting AI to prototype products<br>Gathering data from smart products to improve next generation products on the basis of end-users behaviours |
| | | Servitization | Tracking and monitor the product usage to improve the service provided |
| | | Disassembly | Defining the best and most efficient disassembly path relaying on AI in collaborative robots |
| | | Reuse | Tracking the product to monitor the conditions and evaluate whether the product reuse is possible |
| | | Recycle | Tracking the product to monitor the conditions and evaluate whether and how the product components and materials can be recycled |
| | Process | Waste Management | Tracking the type of material present in the waste to evaluate its recyclability or disposal |
| | | Resource Efficiency | Tracking energy, water, and other resources usage during the production process |
| | | Cleaner Production | Tracking energy, water, and other resources usage during the production process to evaluate possible improvements |
| Meso | Network of firms | Closed-loop Supply Chain | Creating collaboration by mapping the most convenient circular path<br>Forecasting return products quality, quantity, and time |

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|---|---|---|---|
| | | | Tracking products in real-time to estimate the residual value<br>Tracking vehicles to manage the loading of waste and recyclable resources |
| | | Circular Design | Designing the product considering the actors involved in the value chain |
| | | Remanufacture | Tracking the turned back product to monitor the conditions and evaluate whether the product can be remanufactured<br>Exploiting product data, once returned, so to define the best remanufacturing path |
| Macro | Nations, Regions, Cities | Waste Management | Keeping track of circular performance to forecast it in nations, regions and cities<br>Monitoring municipal waste type and quantity |

## 5. CONCLUSIONS AND FUTURE RESEARCHES

The research contribution entails an SLR with the goal to investigate how AI is used to support the adoption of CM strategies at the different scales of adoption (i.e. micro, meso, macro) at the SOTA of scientific literature. In particular, the analysis has been conducted by investigating the potential of applying AI for each strategy and by identifying the provided benefits along a three level scale of adoption. According to the extant literature, AI represents a positive contributor in pursuing the transition from a linear economy towards a circular one. More specifically, its benefits of the different strategies have been highlighted in many contributions (see Table 1). AI and its inherent features provides the possibility to track, analyse and appropriately use huge amount of data tailored to situations which vary in complexity and context. Most of the benefits have been identified specifically while dealing with the micro level which indirectly enhances the intention to adopt specific CM strategies at meso and macro levels, and vice-versa. For instance, the possibility to have a greater monitoring over returned products stimulates companies in designing circular products to facilitate the regeneration of resources. This is also linked to positive stimuli at the macro level. Indeed, having the possibility to manage appropriately the waste generated in cities could be the bridge between companies and policymakers to collaborate towards sustainable actions.

It is worth to mention two main limitations to be addressed in future works. First, it is needed to map the different types of AI adopted for CM, and second to compare the benefits highlighted in Table 1 with the traditional techniques. Moreover, other future research directions are suggested below according to the gaps emerged.

- The synergies between firms, network of firms and policymakers, to exploit the AI benefits aggregated at macro level to stimulate companies' circular products design and production, require further explorations.
- At macro level the focus of the contributions is on the cities, while AI benefits to sustain the circularity of regions and nations have so far remained unexplored. In addition, the strategy widely addressed is waste management while other strategies could be investigated.
- At meso level, AI is used to manage appropriately the reverse flow of products, while the benefits of introducing AI to adopt industrial symbiosis seem little explored.
- At micro level, AI is quite well diffused, especially to perform operating tasks, and it could be further exploited to support the decision-making process of operators concerning the adoption of the different CM strategies.

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