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Article

Industry 5.0 and the Circular Economy: Utilizing LCA with Intelligent Products

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Abstract: While the move towards Industry 4.0 has motivated a re-evaluation of how a manufacturing organization should operate in light of the availability of a new generation of digital production equipment, the new emphasis is on human worker inclusion to provide decision making activities or physical actions (at decision nodes) within an otherwise automated process flow; termed by some authors as Industry 5.0 and seen as related to the earlier Japanese Society 5.0 concept (seeking to address wider social and environmental problems with the latest developments in digital system, artificial Intelligence and automation solutions). As motivated by the EU the Industry 5.0 paradigm can be seen as a movement to address infrastructural resilience, employee and environmental concerns in industrial settings. This is coupled with a greater awareness of environmental issues, especially those related to Carbon output at production and throughout manufactured products lifecycle. This paper proposes the concept of dynamic Life Cycle Assessment (LCA), enabled by the functionality possible with intelligent products. A particular focus of this paper is that of human in the loop assisted decision making for end-of-life disassembly of products and the role intelligent products can perform in achieving sustainable reuse of components and materials. It is concluded by this research that intelligent products must provide auditable data to support the achievement of net zero carbon and circular economy goals. The role of the human in moving towards net zero production, through the increased understanding and arbitration powers over information and decisions, is paramount; this opportunity is further enabled through the use of intelligent products.

Keywords: intelligent products; smart products; Industry 4.0; Industry 5.0; Society 5.0; circular economy; human centric manufacturing; human in the loop; Life Cycle Assessment (LCA)

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1. Introduction

From a paradigm shift that began in 2011 the move towards Industry 4.0 has motivated a re-evaluation of how a manufacturing organization should operate in light of the availability of a new generation of digital production equipment and computer-based systems [1]. The big data revolution has wrought significant change in the service sector, allowing greater understanding of customer needs and additional insights for the development of new products. In an industrial context big data coupled with Internet of Things (IoT) communication technology and the availability of low-cost miniaturized sensors have provided the potential for a new level of awareness on the current status of shop floor machine and robot operation and the establishment of a real time picture of production status available to workers and management alike. Advances in production machine and industrial robot control through the use of Artificial Intelligence have led to new automation solutions for the production line, with some authors forecasting the prospect of the fully autonomous 'lights out' factory to become the norm rather than the exception (moving beyond the automation of low complexity repetitive processes). This paper highlights a new emphasis in the use of technology, specifically intelligent products, for automation solutions that include humans in the loop of decision making, the enablement of knowledge skills and the facilitation of creativity throughout the manufacturing organization.

In noting a move from Intelligent Manufacturing to Smart Manufacturing (both paradigms are in use in Industry 4.0 implementations) the utilization of AI to integrate 'human intelligence/wisdom in manufacturing' is seen as lacking by [2] in the former paradigm. Wang et al. [3] highlight a need for further consideration of human skills in both Smart and Intelligent Manufacturing paradigms, these authors suggest that humans can work alongside robots rather than being replaced by automated systems. The EU (European Union) [4] highlights this refocusing from current manufacturing automation to more human inclusive technology as a major paradigm shift, that has been collectively named Industry 5.0. They go onto identify three major focus areas that may feature heavily in the manufacturing research and development landscape over the next 10–15 years: (1) Sustainability—reductions in energy consumption, reduced CO_2 output, waste reduction and greater reuse and recycling of materials in a circular economy; (2) Resilience—more robust processes and plant to be developed and employed in industry, more resilient supply chains; (3) Human centric approach—human interests are the core focus of production, technology enables workers in industry aiding and advancing their skills and knowledge [2]. Xu. et al. [5] highlight the shift from a technology focus to that of values in the Industry 5.0 concept, noting its ambition to "achieve societal goals beyond jobs and growth..." placing "the wellbeing of the industry worker at the center of the production process". Mourtzis et al. [6] make the point that technology use in Industry 5.0 must enable the "physical to digital to physical loop..." which is necessary to "ensure the long-term growth of a society centered on people". It is clear that Industry 5.0, as a concept, is now forming and attracting the attention of both industry and wider society [4,6–8]. Human centricity and environmental sustainability issues are the focus of Nahavandi [7] in their research on the emerging Industry 5.0 agenda. This author argues that AI in combination with human participation can have the power to address many of the environmental issues associated with product production whilst focusing on human needs [4]. The topic of human centricity in artificial/digital systems is also expressed as 'human in the loop', where people are actively engaged in decision making activities or physical actions (at decision nodes) within an otherwise automated process flow. Human in the loop has much relevance within the Industry 5.0 agenda and has been explored by a number of authors with regard to its relevance within a manufacturing setting [9–13].

Many of the Industry 4.0 technologies, currently used for automation, can in many cases be further adapted to aid human workers in more efficient production practices whilst unlocking their knowledge and creativity and addressing gaps they may have in their personal skillset (shown in Figure 1). Whilst acknowledging the increased prominence workers may take in high technology and automated manufacturing scenarios of the future the same digitally enabled systems can also address human centricity and sustainability goals in terms of the customer base in the way products are produced. The design of production line robots and machinery is now receiving attention from interests in the human factors field, where robots are designed to cooperate with humans in the completion of tasks [14–21]. A particular area of growing interest within this field is that of Collaborative robots or Cobots [22–24].

Mass customization is very much an established trend in manufacturing and its sophistication and achieved levels of efficiency have been made possible in no small part through the use of technologies described by the Industry 4.0 paradigm. An evolution of this trend can be found in mass personalization or the 'market of one', whereby products are developed to suit individual customers parameters and may even involve the customer in the design process for the product (co-creation) [25,26]. Mass personalization also has the aim of addressing issues of sustainability though the reduction of waste and material used in the production process.

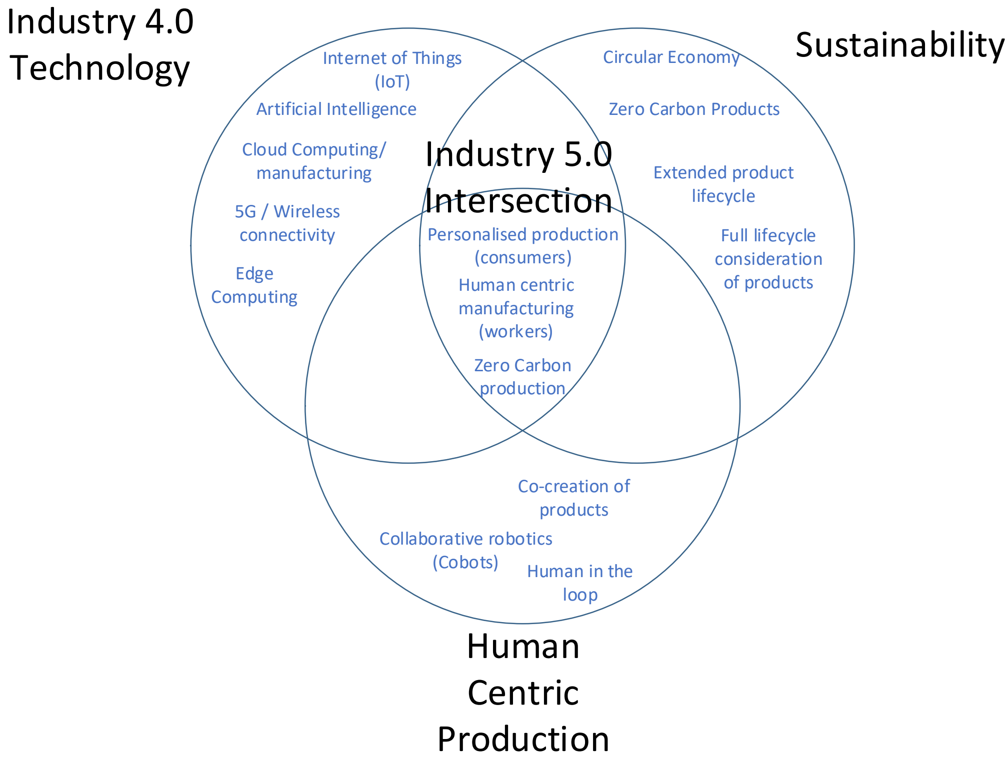

Figure 1. Human Centric Manufacturing: Industry 5.0 Intersection of research areas.

It is argued by authors such as Rojas et al. [27] and Marcon et al. [28] that the movement to the use of pervasive digital technology as demonstrated in Industry 4.0 for the enhancement of human inclusive industrial tasks can be utilized to address wider societal challenges. This paradigm shift has been called Society 5.0, originating from an initiative of the government of Japan Society 5.0 aims to utilize digital and Cyber Physical Systems (CPS) to address issues of sustainability, the management of energy and transportation infrastructure systems and inclusiveness of social policy issues within wider society [28–31].

The quantification of the improvements or changes with respect to environmental impacts, resource usage, waste and/or economic costs, is a key contributor to the implementation of a successful Circular Economy (CE) strategy. The CE concept was initially defined by Pearce and Turner [32] as an economy where waste produced from one process is used or recycled as feedstock for another process. In later work Geissdoerfer et al. [33] examine the Circular Economy in relation to industrial practice highlighting the factors 'long-lasting design, maintenance, repair, reuse, remanufacturing, refurbishing, and recycling' as important in the application of this concept within the sector. Life Cycle Analysis (LCA) has also been proposed as a tool for the long-term holistic assessment of the effectiveness and impacts associated with CE strategies and it can help identify unintended consequences associated with a change in different processes [34]. As sustainability demands increase, there is a greater need for transparency and a harmonization of methodologies for LCAs to assess if any given CE output does fulfil the goal of reducing environmental and social impacts [35]. LCA is an important basis and addition for CE. It offers an analysis of the advantages or disadvantages of CE on a product or service level, then it identifies the possible development alternatives along the life cycle. Based on the LCA results, it is possible to determine the business strategy goal with the aim of moving towards a circular economy [36].

The disassembly process plays a key role in the sustainable End-Of-Life (EOF) treatment of Waste Electrical and Electronic Equipment (WEEE) [37]. As the manual disassembly of products is time-consuming, robotic disassembly has been widely utilized in manufacturing for improving the efficiency of recycling, and each workstation is usually assigned for one single task. However, there exist significant differences in product volumes and lot sizes between different manufactured products as well as product variants with different lifespans [38]. An adaptive and robust automation line is required instead of the traditional rigid design which is independent of human knowledge [39].

The Ellen McArthur Foundation [40] makes the case for the use of intelligent assets in achieving circular economy objectives. In Morlet et al. [40] the case is made for the use of sensor systems to provide information on how assets are performing along with the compilation of data on materials use and potential for recycling. The extension of this aim to intelligent products is compelling, especially in light of the increasing need to decarbonize manufacturing. In this paper a number of topics, methods and acronyms have been used, Table 1 below provides a summary explanation of the notions and terms that are central to this research.

Table 1. Summary of terms used in the paper.

Term	Explanation
IoT	Internet of Things—The Internet protocol is used to provide interoperability between physical computer processor and equipped objects and distributed digital information systems, often realized through wireless connectivity
Cobot	Collaborative Robot—robots that work alongside humans in a safe collaborative capacity to achieve partial automation [22]
CPS	Cyber Physical System—A combination of digital systems, services and machines (including industrial robots) to provide intelligent and automated control of physical assets (though the use of IoT and Artificial Intelligence technologies)
Digital Twin	Digital representation of a physical asset, such as a machine, produced by utilizing sensor data streams provided by the asset and displayed to the user in a form a static or animated graphics based visual representation detailing the assets real time functioning
Circular Economy	A paradigm that encourages industry and society to move away from the current ‘take, make, dispose’ model of production through reuse, remanufacture or recycling of materials [40]
LCA	Life Cycle Analysis—a method used to estimate the potential environmental impacts of a given product or a service [36].
Dynamic LCA	An LCA in digital form, connected in real time to physical assets that are being monitored
WEEE	Waste Electrical and Electronic Equipment
Intelligent Products	A product equipped with an ability to monitor, assess and reason about its current or future state [41]
RFID	Radio Frequency Identification—functionality provided though RFID tags, allowing digital information to ‘read’ by radio transmitter-receivers (used to describe objects that the tag is attached to)
Edge Computing	Processors and sensors that are incorporated or mounted on assets to be monitored, capable of processing data locally before transmitting the results to remote and distributed data hubs for the generation of further consolidated analytics
HRC	Human Robot Collaboration—a robot that requires collaboration from a co-worker to achieve partial automation
GHG	Greenhouse Gas—such as Carbon Dioxide $\mathbf{CO_2}$ contributing to global increases in temperature (Global Warming)

In Section 2 of this paper the research methodology is set out, describing the range of literature consulted in the formation of the proposed model of dynamic LCA for Intelligent Products and pertinent research questions that have led to the development of the aforementioned model. Section 3 provides an overview of intelligent products and illustrates sustainability focused extensions to the functionality they provide. Section 4 details methods to support human robot collaboration for product disassembly. In Section 5 the use of LCA in formalizing the sustainable through life consideration of Intelligent Products is outlined. The paper concludes with the proposal of an ambitious research agenda to further the development of intelligent products and embed their role in delivering a new generation of decarbonized manufactured goods.

2. Research Methodology Utilized

This work has been produced in accordance with a structured process involving an evaluation of existing research literature. The initial questions that this research set out to explore and investigate focus on the roles that Intelligent Products could play in realization of sustainable human centric manufacturing. Research questions posed were:

RQ1: What is the current definition of intelligent products today and what functionality might they provide in the near future?

This question considers the current functionality exposed by intelligent products currently available on the market and how the functionality set can be further developed. The potential for the addition of new data parameters, sensing capabilities and human interactivity possibilities are sub questions that are also in scope.

RQ2: What forms of sustainable, circular and human centric manufacturing and maintenance processes may emerge through the utilization of intelligent product functionality?

Can Intelligent products aid the emergence of new sustainable methods for maintenance and the improved utilization of both human and machine inputs?

RQ3: Is it possible to envision a model for dynamic LCA utilizing the current and future functionality of Intelligent Products?

Can a holistic view of manufactured products carbon value and environmental impact from a full lifecycle perspective be provided? With sub questions to be considered such as: Can intelligent products take an active role in their end-of-life treatments?; What additional functionality and information would such products need to dynamically share with machines and humans and in what form?

In the completion of this research the literature review process shown in Figure 2 was followed to arrive at the final set of papers to be analyzed. A number of search terms were used for the identification of relevant papers (as shown in Table 2). The search terms were derived from an initial review of the current topics in manufacturing automation. This was then focused to the topics seen as most relevant by the authors and informed by literature.

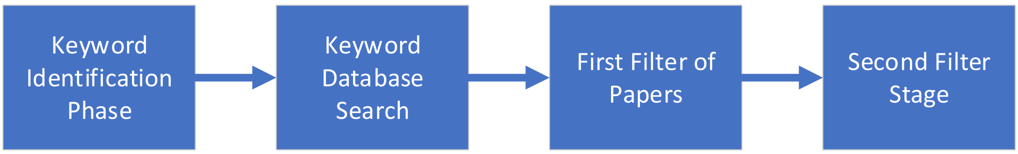

Figure 2. Process followed for the completion of the literature search stage.

Table 2. Paper keywords and time periods considered.

Keyword	Selected Time Period
Collaborative Robotics for Disassembly	Year 2010–2022
Intelligent Products	Year 2000–2022
Smart Products	Year 2000–2022
Human in the loop Manufacturing	Year 2010–2022
Human Centric Manufacturing	Year 2010–2022
Life Cycle Analysis in Manufacturing	Year 2000–2022
Circular Maintenance	Year 2010–2022

The publication database consulted was Scopus with relevant papers indexed between 2000 and 2022. In addition, the Web of Science and Scholar databases were used as comparators to identify additional works not found by Scopus. Table 3 shows the search terms and the peak paper publishing year followed by the number of publications in 2021.

Table 3. Papers returned after first filtering stage.

Search Term	Peak Year	Published in 2021	Total
Collaborative Robotics for Disassembly	(2021) 7	7	21
Intelligent Products	(2021) 61	61	575
Smart Products	(2021) 148	148	895
Human in the Loop Manufacturing	(2016) 8	4	25
Human Centric Manufacturing	(2020) 6	4	35
Life Cycle Analysis in Manufacturing	(2021) 7	7	45
Circular Maintenance	(2021) 15	15	63

In order to limit results to just relevant papers the 'PRE/' term was used with a combination of 0 to 10 intervening words allowed between the searched for terms (to ensure the two search terms were found in contiguous fashion):

TITLE-ABS-KEY (Intelligent PRE/10 Products) AND PUBYEAR > 1999.

The only exception to this was 'Collaborative Robotics for Disassembly' where the AND operator was sufficient.

This first filtering of the papers helped to establish which works were most relevant to the questions posed in this study. A second stage involved further filtering with additional attention given to papers that were more likely to contribute to the development and/or use of intelligent/smart products as active contributors to sustainable production and consumption. It was also the case that additional weighting was given to more recent papers (post 2015 publication date) leading to a predominance of such works in the completed review. As can be seen in Figure 2 certain subject areas contain a higher proportion of recently published papers than others. This stage involved the rapid analysis of abstract, introduction and conclusions (including findings and future research) for each paper. This second stage reduced the overall total amount of papers from 1659 to 206. The final stage of the literature review commenced with the full reading of the remaining papers reducing the total to just over 100 relevant works for inclusion. At this stage, in-depth analysis of the remaining papers involved an assessment of the contribution and relevance of the publication and its impact factor rating (as rated by Clarivate).

From the review stage it was clear that the rise of Intelligent products has provided a new and potentially extensive source of detailed usage and status data for manufacturers. In utilizing this information for improved product lifecycle aims and maintenance practice, consistent with Circular Economy goals, the need for the integration of human skills and knowledge has become evident in order to deliver a step change in the manufacture, maintenance and end of life treatment of products such that they exhibit a vastly reduced carbon footprint, The position established by the review stage demonstrates the need for a dynamic system of holistic assessment of products throughout their lifespan, it is put by this research that the Dynamic LCA concept can play a vital role in the achievement of this goal.

3. Intelligent Products

A range of definitions are available for the concept of an Intelligent product. McFarlane et al. [41,42] asserts that 'an intelligent product is equipped with an ability to monitor, assess and reason about its current or future state and if necessary influence its destiny. McFarlane et al. [42] go onto describe the Intelligent product being permanently associated with self-describing information, which may be read via electronic sensing (in the case of [42] this is enabled through the use of wireless RFID (Radio Frequency Identification tags). Meyer et al. [43] identify three particular dimensions: (1) the intelligence capability of the product; (2) the location of the intelligence; (3) whether the product is a single entity or part of an aggregate. Meyer et al. [43] underline the importance of defining how intelligence is enabled through embedded processing and utilized throughout the product lifecycle. Yang et al. [44] note that the intelligence of products may be leveraged throughout their life, with their information stored in or accessible to distributed data repositories. In describing the types of data provided by intelligent products as a set of discrete 'services', Yang et al. [44] motivate a spectrum of added value support systems that may be provided alongside; ranging from remote diagnostic services, relating to product health, to in-use data, and end of life treatments. Sallez et al. [45] also give focus to the potential recycling stage of an intelligent product, finding that augmenting products with information can assist in detailing their material composition (which can also be leveraged by remanufacturing and reverse logistics processes).

The circular economy provides a wider context and outlines a framework for sustainability considerations for manufactured products in a move away from the current 'take, make, dispose' model of production [40]. The rise of the Internet of Things (IoT) has led to greater interoperability between physical products and distributed digital information systems, often realized through wireless protocols [46]. Morlet et al. [40] suggest that the actual lifespan of an intelligent product (or asset) may be extended by knowing its current health and allowing it to decide its own maintenance needs and schedule; this can be taken further with the use of artificial intelligence to predict when maintenance may be required in the future [13]. The decision process of when to take a product out of service and select an appropriate treatment can also be enhanced through intelligent product knowledge; decision options may include a choice of: product re-use in other less demanding role; remanufacture of the product; product recycling [40]. Intelligent products may be offered in combination with services, such as maintenance contracts, in a process known as Product Service Systems (PSS) [47]. Alcayaga et al. [48] provide an initial exploration of intelligent product and PSS combination to aid a lifecycle consideration of the product in terms of its sustainable treatment. In the design stage of new products, the performance of existing products 'in use' can inform the development process along with data regarding its end-of-life treatment or further reuse cycles [49]. The employment of Digital Twin representations can be used to investigate and facilitate the reconfiguration of products. Abramovici et al. [50,51] employ a Digital Twin to enable reconfiguration of a product based on its 'in use' data and provide real time adaptations. Kerin and Pham [52] explore the process of remanufacturing and the changing nature of technology use in this sector; in employing smart robotic cells for remanufacturing this paper sets an agenda that may be complimentary to the movement towards intelligent product development, potentially allowing communication between products being worked on and the machines performing the work.

Intelligent products are also referred to as Smart Products by some authors [46,48,53–57]. Intelligent or Smart products may take part as components of a Cyber Physical System, due to their IoT 'connected' capability [58–60]. An argument could be made that in achieving greater use of electronics with manufactured products as a whole will lead to increased resource use at the production stage and additional waste at the end of life. In terms of electronic waste Li et al. [61] envisage a unified set of standards towards the treatment and recycling of WEEE (Waste Electrical and Electronic Equipment) in order to eliminate the 'dumping' of such potentially highly polluting materials in 3rd party countries. Though perhaps it is through the redesign of existing electronic products that the most gain can be made in this direction. Meloni et al. [62] make the point that the design of consumer electronics products must take account repair and recyclability of the internal components and consider the potential for modularity in the design. Yang et al. [63] explore the possibility for foldable paper-based electronics that are less demanding of raw materials and hold the potential to be easier to recycle. In addressing the aforementioned concerns reference must be made to progress in both the material composition and nature of electronics for sensing and processing within intelligent products.

As can be seen in Table 4 the timeline for intelligent products takes in many of the major technological developments in sensing, processing and wireless internet connectivity over the past 20 years. It is the opinion of the authors of this paper that while technology will continue to advance in terms of processing power and miniaturization (among other factors) it is the ability for such products to play an active role in meeting sustainability goals that is perhaps one of the greater opportunities over the next 5–10 years. While being able to monitor energy use many intelligent products functionality could be extended to provide a dynamic carbon footprint calculation. It is also the case that such products are capable of taking an active part in the management of their own lifecycle such as: advising on repairs and the need for replacement parts; end of life treatment of parts to be replaced or whole product itself; energy use monitoring and reporting to users/consumers and manufacturer; advising on process(s) to be used by maintenance operatives with live feedback.

As can be seen in Figure 3 below an outline of an intelligent product, in the form of an electric vehicle, is given. Figure 3 shows that the constituent components of an intelligent product may also be intelligent and able to communicate with each other in a product wide wireless network. Such a system may further aid the maintenance operative by performing a root cause analysis, utilizing onboard AI algorithms to autonomously diagnose faults utilizing the internal network communication. The traditional Fishbone or Ishikawa diagram utilized in root cause analysis may be generated and reproduced in completed form for the maintenance operative as part of the reasoning for the fault diagnosis. This approach utilizes the notion of Explainable AI (XAI), where automated systems additionally 'employ machine intelligence and learning techniques to provide explanations in order to justify the trust Humans are required to invest in such software-based entities' [67]. It may also be seen in Figure 3 that capacity is given to the intelligent product to attempt self-repair or in some mode also 'take part in' or assist with a manual repair. Radio Frequency Identification (RFID) tagging of components is still possible in this model, to identify and also detail recycling and end of life treatments for individual components, along with communication of 'in use' data to remote 3rd party Cloud datastores for further processing/use by manufacturers and other agents. The use of miniaturized and wireless connected Edge processing units allow this additional level of dynamic interactivity as described to take place on an individual product and component level.

Table 4. A Timeline of Intelligent Products Development.

Timeline	Concepts Developed	Key Papers
RFID 2000–	• Product can retain self-describing information and is capable of communication • First generation of product driven manufacturing control concept—product communication with production process • Smart products • Ambient Intelligence (AmI) • Products as services	McFarlane et al. [41] provided an initial definition of an intelligent product and lay the foundations for RFID integration and use with such products.
		Mühlhäuser [53] provides a definition of smart products in this work along with the term 'active knowledge' referring to the capability to exhibit autonomous behaviours when such products are in use by humans.
		Allmendinger and Lombreglia [64] describe connected products being able to communicate their status and send, receive and perform basic data processing actions; a discussion is also presented on product and service combinations.
Cloud/IoT 2010–	• Coordination of product data with cloud-based data sources—Product history is available and distributed processing of data • Semantic technology use with intelligent products • Sensor networks and IoT technology use • Embedded processing • Artificial intelligence integration • Personalization • Intelligent product Lifecycle consideration	McFarlane et al. [42] revisit the term 'product intelligence' in the light of technology changes in supply chain and logistics operations.
		Sabou et al. [65] examine semantic technology use with the smart product concept and the notion of ambient intelligence.
		Kiritsis [49] provided an in-depth study of product lifecycle management (PLM) with intelligent products and proposed a standard in the form of a semantic ontology for PLM.
		Sallez et al. [45] examine intelligent products and PLM from 'design, manufacturing, distribution, use and recycling' stages and introduce the concept of the active product.
		Meyer et al. [43] describe the distributed nature of data processing possible with intelligent products
		In Yang et al. [44] the acquisition of lifecycle data through a service based infrastructure is put forward, this author highlights the importance of the knowledge base of past activity to this approach.
		Anderl et al. [54] describe the use of embedded systems and products as part of Cyber Physical Systems.

Table 4. *Cont.*

Timeline	Concepts Developed	Key Papers
Edge and Sensing 2020–	• Human centric production • Edge computing—integrated information sensing and processing • Cyber Physical Systems and Intelligent Products • Digital Twin Integration • Circular Economy	Barbosa et al. [59] propose a combining of the intelligent product concept with that of Cyber Physical Systems (CPS) and provide an illustrative case study from the white goods industry.
		Romero and Noran [57] propose the notion of the 'Green Sensing Virtual Enterprise' bringing together Circular Economy Cyber physical Systems and Smart products and intelligent assets, emphasizing the dynamic nature of sensing possible with IoT technology.
		Alcayaga et al. [48] envisage integrated smart products and circular product service systems, highlighting the need to link into a wider range of end-of-life options such as remanufacturing and re-use.
		Abramovici et al. [50] introduce the notion of a virtual twin (Digital Twin) of a smart product allowing dynamic reflection of changes between physical and digital representations, pointing to the need for semantic standards to enable further levels of product service system based interoperability.
Sustainable Products 2025–	• Dynamic LCA for intelligent products and their manufacture • Dynamic Carbon footprint calculation • Recyclable electronics for Sustainable intelligent products (full circular lifecycle of intelligent products)	Kerin and Pham [52] explore the process of remanufacturing and the changing nature of technology use in this sector, employing smart robotic cells for remanufacturing.
		Ren et al. [66] provide an extensive review of data analytic approaches to current and future product lifecycle challenges.

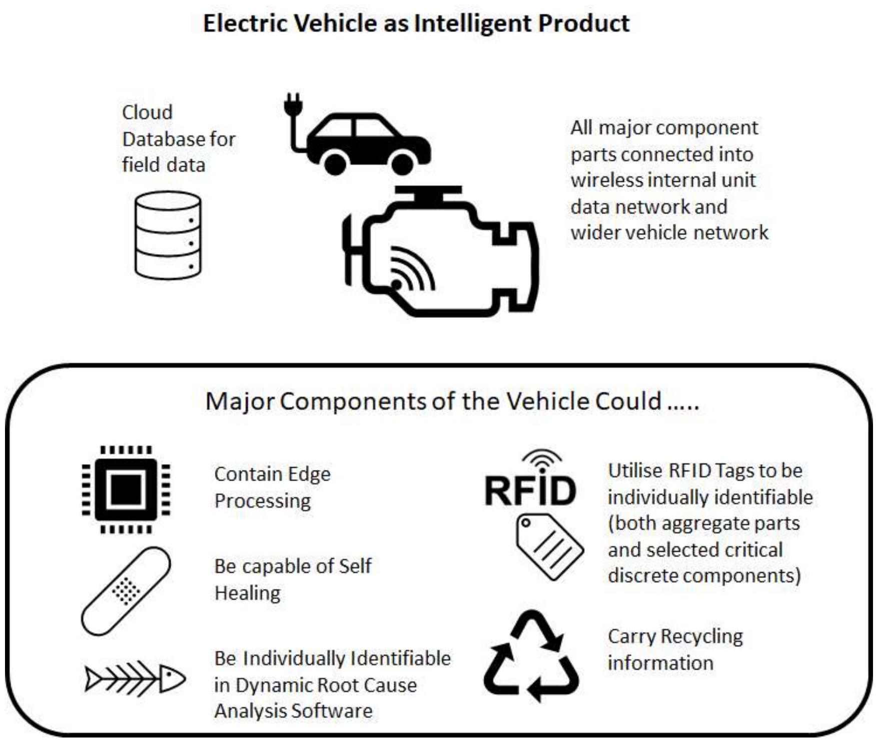

Figure 3. Electric Vehicle as an Intelligent Product (adapted and extended from the intelligent product illustration of [68]).

4. Human Robot Collaboration for Disassembling Products at End of Life

Human–Robot Collaboration (HRC), whereby the robot requires collaboration from a co-worker to achieve partial automation, provides a new direction for disassembly operations. A human in the loop scenario in which the system becomes more capable of performing diverse tasks through the facilitation of workers cognitive and physical abilities; while taking advantage of the capability of the robot to perform repetitive tasks [67].

Current research in HRC applied to disassembly processes often considers the safety of the human partner by fusing sensor features with the human in the loop concept. For example, Büker et al. [69] integrated the vision-based control system with a force sensor and custom-made unscrewing tool to build a safe robot system for wheel disassembly. Gerbers et al. [38] also studied the safety measurement with 3D vision system for Lithium-Ion Batteries disassembly. Roda-Sanchez et al. [70] compared the 3D vision system and wearable Inertial Measurement Units (IMUs) based system for efficient and robust human recognition. Moreover, another research direction is to make robust and flexible decision process by integrating cyber-physical production system (CCPS) and Artificial-Intelligence (AI) technology. Zussman and Zhou [71] proposed an adaptive planner utilizing a Petri Net approach. Liu et al. [72] built a complete system by integrating CCPS with AI methods including perception, cognition and decision making. In addition Prioli and Rickli [73] proposed a cloud-based collaborative architecture for critical materials disassembly for electronic devices. Huang et al. [74] adopted active compliance control for robot to dismantle a press-fitted water pump. Another direction that is gaining in popularity is the application of the Learning from Demonstrations (LfD) methodology. This methodology can also improve the learning efficiency of the Collaborative robot (Cobot). Bdiwi et al. [75] provided informative demonstrations from a supervisor perspective to a robot, enabling the transfer of demonstrations and skills from a human to a robot for unknown parts disassembly. This line of research is supported by Vongbunyong et al. [39], this research enabled a skillful worker to demonstrate correct disassembly sequences to a robot for replication, in effect transferring knowledge to the Cobot.

Increasingly robot implementations exist within an ecosystem of automated production machinery, often capable of data acquisition through advanced sensing and wireless control from remote locations via. Cloud technologies, referred to as Cloud Manufacturing by authors such as Liu et al. [76] and even Cloud Robotics [66,77–80]. Such a Cyber Physical System (CPS) is often the realized outcome when implementing Industry 4.0 solutions within modern factories. Grau et al. [81] set the scene for a future manufacturing environment where open questions remain about the role of humans and their ability to remain 'in-the-loop' of decision making in highly automated production lines. Romero et al. [82] make the case for 'Operator 4.0', whereby human participation in industrial job roles are enabled though cooperation with intelligent machine and robot systems. In proposing a typology composed of 8 operator functionality aspects (Super-strength; Augmented; Virtual; Healthy; Smarter; Collaborative; Social; Analytical), Operator 4.0 is seen as a way to augment human skills rather than seek labor removal and fully automate complex industrial tasks [82]. In addressing the emerging Industry 5.0 agenda Romero et al. [83] identify that workforce resilience, where human worker needs are recognized, can co-exist with the production system when realized as a 'symbiosis' of human–machine cooperation. Clabaugh and Matarić [84] set an agenda for the personalization of human robot interactions in the areas of medical, care provision and human learning. In recognizing the role of Machine Learning Clabaugh and Matarić [84] highlight the role human can play in the development of more assistive robots though interactive machine learning and a 'human in the loop' approach to the machine-person relationship. Leng et al. [85] also highlight the central aim of industry 5.0 as the recasting of industrial employment in terms of improved well-being and empowerment of workers through assistive technology. This relationship is also emphasized by Weiss et al. [86] who note, currently, that a lack of role clarity surrounds such interactions in the context of Industry 4.0.

It is the opinion of the authors of this paper that intelligent products may play an active part in their own disassembly. Utilizing inbuilt guidance and processes, Cobots and humans can be informed on correct procedures. It is also the case that once end of life and recycling information is provided by intelligent products enhanced procedures may be followed in the act of disassembly to respect the optimal course of action in terms of overall sustainability and carbon reduction goals. The question remains on what types of recycling information an intelligent product should contain and the need for an overarching methodology for the generic specification of parameters and holistic management of the products lifecycle. In the next section the use of Life Cycle Analysis (LCA) is proposed along with a model for its use with informated goods such as intelligent products.

5. LCA and Sustainable Intelligent Products

Sustainability, where there is ever more attention placed on the long-term impact of manufacturing processes, is likely to be a major focus area of manufacturing and product development over the next couple of decades [3]. Reducing Greenhouse gases (GHG) is a core component of sustainability and is a key driver of activity in organizations seeking to achieve net zero carbon emissions.

In 2021 there was a significant increase in global and national mandatory reporting frameworks such as the Taskforce on Climate-related Financial Disclosure (TCFD) and the European Sustainable Finance Disclosure Regulation (SFDR). In addition, in the run up to and post COP26 in Glasgow in 2021, increasing numbers of global and local organizations have been committing to reporting to voluntary frameworks such as the Carbon Disclosure Project (CDP) and the Principles for Responsible Investment (PRI). Organizations are also increasingly committing to set robust Science Based Targets accredited by the Science Based Target initiative (SBTi). These all require an assessment of and reporting of all greenhouse gases across not just the traditional scopes 1, 2 but also scope 3. Robust scope 3 data gathering, calculations and reduction plans are therefore a new requirement for many organizations (Scope 1 emissions are direct emissions normally produced by fuel combustion; scope 2 emissions are indirect emissions produced by 3rd party energy providers such as the electricity providers of industrial organizations; Scope 3 emissions are also indirect and produced as part of the value/supply chains of organizations). In January 2022, post COP26, net zero carbon proposals, declarations, pledges and legally binding commitments covered 90% of global GDP and 85% of the world's population [87].

For most manufacturing companies, 70–80% of their overall carbon footprint is in their scope 3 GHG emissions, and more specifically will reside in their 'purchased goods and services' category, i.e., in their supply chain [88]. Therefore, industry 5.0 will have an increasing focus on decarbonizing supply chains. This will impact decision making at all stages of the industrial manufacturing process. Manufacturing organizations are being asked by their clients to provide data on their GHG emissions and whilst the majority of the scope 1 and 2 data is known and accurate, the majority of scope 3 data is currently estimated.

Moving from estimated to actual scope 3 GHG data for manufacturing organizations initially requires engagement with suppliers to acquire their GHG data, and often will require Life Cycle Assessments of key products.

Life Cycle Assessment (LCA) is a standardized analytical method (ISO 14040) [89,90] designed principally to estimate potential environmental impacts associated with a product or a service. The goal of the process is to evaluate the environmental burdens associated with a product, process, or activity by identifying and quantifying energy and materials used and wastes released to the environment; to assess the impact of those energy and materials used and releases to the environment; and to identify and evaluate opportunities to realize environmental improvements [91].

The assessment includes the entire life cycle of the product, encompassing all the resources required and pollutants emitted throughout all stages of its life cycle, "from cradle to grave", i.e., from raw material extraction, construction and use to waste management and recycling or disposal [92]. It provides a complete view of connections between production systems and the environment. The LCA method consists of four interrelated phases: goal and scope definition, Life Cycle Inventory (LCI) analysis, impact assessment and interpretation of results [90]. LCA could help reaching a variety of goals, from helping short-term process engineering to supporting long-term strategic planning. LCA also motivates process optimization and product improvement, and it allows a transparent comparison between different product designs. A specific type of analysis, modelling and data quality is required to achieve each of the goals. The environmental effects or impact categories in an LCA represent the consequences of a physical interaction between a system studied and the environment. The most used categories are: Global warming potential; Ozone depletion; Acidification; Eutrophication; Resource depletion; Human toxicity; Ecotoxicity; Photochemical oxidation; Land use.

The Dynamic LCA for Intelligent Products

Human consideration of LCA and embedded carbon value and output is necessary as it is not possible at present to envisage a totally autonomous production system, let alone one with additional capability to dynamically minimize or remove carbon emissions in its operation. The ability to cascade environmental considerations and sustainable processes throughout the manufacturing organization and customer base requires human centric technology and visualization techniques to aid understanding and augment decision making to achieve a circular and net zero carbon economy.

In Figure 4 the outline of a dynamic model for LCA utilizing intelligent products is detailed. As can be seen in Figure 4 carbon emissions may be produced at the stage of raw material extraction/processing, in manufacturing, in use and at the end of life of a product. For an intelligent product, as described earlier in Figure 3, opportunities could exist to utilize on board processing capabilities and Artificial Intelligence to provide data relating to embedded carbon, emissions and energy use at every stage of the products life. A dynamic LCA could be provided to manifest the carbon total of a product to date and predicted end of life total.

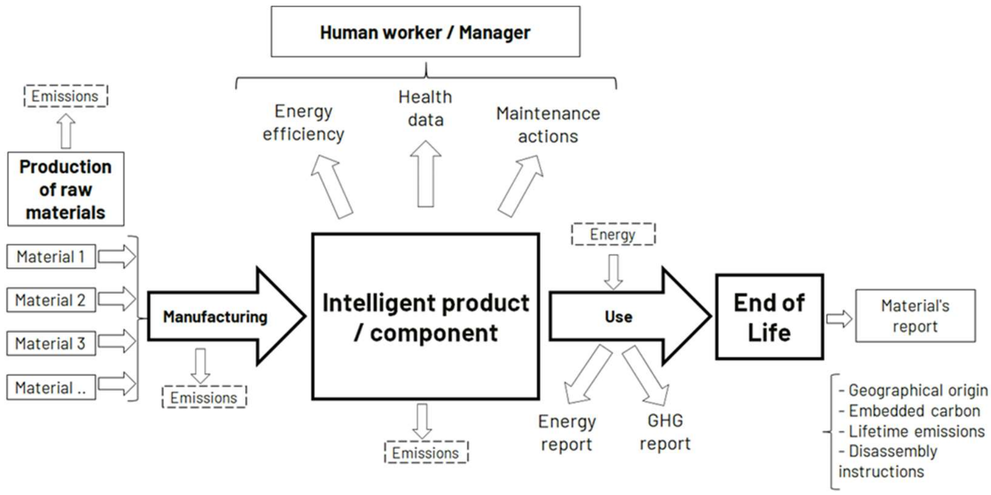

Figure 4. The intelligent product as dynamic provider of data for a dynamic Life Cycle Assessment (LCA).

Table 5 shows the range of information that an intelligent product/component could hold and actively communicate to other entities. In engaging with an LCA agenda the Intelligent product would need to hold information on the materials it is made out of and the carbon embedded in the product/component and released during its manufacture. Similarly whist in production the amount of carbon emitted in production may be recorded by the product produced. Whilst in use an intelligent product may report its energy use patterns back to the manufacturer (not just the consumer) and estimates made of carbon emissions produced. At end-of-life stage the product is able to provide a manifest of constituent materials and their geographical origin, embedded carbon and lifetime emissions estimate, along with suggested disassembly instructions.

For the human worker or manager in manufacturing the intelligent product can communicate health data throughout its life (the capture and relay back the manufacturer of such data is especially interesting for the new product development team). It can also relay information about itself whist in the manufacturing stage and at end of life communicate about its disassembly. In use fault data can also help inform maintenance actions and be communicated through a smart component internal network which, through the addition of artificial intelligence techniques and edge processing, may be capable of undertaking basic route cause analysis to trace and describe internal faults more accurately. The ability to perform dynamic root cause analysis may act as the basis for more accurate fault reporting to the customer. The customer will also want to know about energy use of the product whist in operation. At the end of a product's life the imminent replacement need could be indicated to the customer and the manufacturer, this is especially pertinent where the product is rented out to the customer, in a product-service type arrangement, rather than sold to them. In the manufacturing setting the Procurement manager also needs clear guidance on the carbon content of materials and the emissions required for their extraction/manufacture so that decision making on which component to purchase can be improved in the direction of sustainability concerns. In summary, provision of the information required for Table 4 would address one of the main limitations experienced in current LCA implementations, that of data access [34]. For the designer the understanding of the environmental impact of individual materials can help in making decisions about product composition and may lead to better decisions regarding dematerialization of products (regarding the number and amount of raw materials used to manufacture a product). Material passports for manufactured goods and components have been proposed for use in the construction sector to create inventories of building components utilized in a given project [93,94]. The notion of such a passport for general manufactured products have been put forward by Spring and Araujo [95] in the form of a 'product biography, describing a linked data set recording how a product is 'repaired, refurbished, upgraded'...'dismantled, reassembled and discarded'. Adisorn et al. [96] take the view that the material passport is just one of four information tools that are available to describe product parameters relating to circular economy goals, comprised of: Energy Label; Material Passport; Cradle-to-Cradle passport (C2C); Asset Administration Shell (AAS). Adisorn et al. [96] go onto define a Digital Product Passport that seeks to both complement and streamline current models for product descriptions and ease communication between actors such as repair facilities and recyclers. Table 5 below demonstrates a parameter set that could be used in both the immediate (short term) and long-term monitoring of parts relating to an electric vehicle; the implications of the data they provide may be assessed within a Dynamic Life Cycle Assessment (as described in Table 6 with parameters developed from the work of [97]).

Table 5. Intelligent Product Information provision for Life Cycle Analysis, Manufacturing Workers and Customers.

	NPD and Design	Manufacturing/ Assembly Stage	In-Use Stage	End-of-Life Stage
LCA Need	Intelligent products to report material content and geographical origin of materials	Dynamic calculation of carbon emissions from production process	Dynamic reporting of carbon emissions to manufacturer	Intelligent products to report material content and geographical origin of materials
Human worker/manager need	Embedded carbon content of intelligent components and fully assembled intelligent product Components to report health data and faults to manufacturer	Intelligent components report health data and correct assembly/integration instructions to production line workers, production supervisors and managers Dynamic root cause analysis reported to manufacturer–with full reasoning availability (utilizing XAI to provide analysis and decision reasoning in the form of text/process flow chart	Intelligent components report health data and faults to manufacturer Dynamic root cause analysis reported to manufacturer–with full reasoning availability (utilizing XAI to provide analysis and decision reasoning in the form of text/process flow chart)	Dynamic inventory production of end-of-life materials for reverse logistics disassembly (possibly via. product service style 'rental' contract with between manufacturer and customer)
Customer/end user need	Improved fault communication and display with faults to be reported to customer and manufacturer Dynamic reporting of energy consumption/resource needs for daily operation	Dynamic root cause analysis reported to manufacturer–with full reasoning availability (utilizing XAI to provide analysis and decision reasoning in the form of text/process flow chart)	Dynamic reporting of carbon emissions to customer and manufacturer Improved fault communication and display with dynamic root cause analysis to customer utilizing plain text explanations (made possible through XAI)	Indication to customer that maintenance/repair of intelligent product or replacement is imminent

Table 6. Intelligent Product Information Parameters for an Electric Car.

Parameters Required	Dynamic LCA Implications
Fault indicator	Fault warning system should be regularly tested and replaced if faulty. Replace and recycle option may be necessary
Part history	Data from vehicle can inform long term trends relating to the performance of specific parts
Model of average driving conditions	Vehicle in motion data combined with route taken, road conditions and weather can assist in developing usage models when mapped to part maintenance needs.
Electric Current supplied by battery	Monitoring of current within battery pack can provide early warning of drops in battery performance and potential faults.
Temperature	High temperature may indicate a critical fault with the battery pack, temperature trends combined with driving conditions data could provide early warning of faults developing
Acoustic emissions from major moving part components	Part can be maintained (e.g., greased) to reduce wear; if faulty the part can be replaced and remanufactured or recycled if faulty.
Range and car recharging trends	On board processing showing 'economy' trends of vehicle when in motion may be further analyzed to detect early warning signs of reductions in battery performance

6. Discussion and Research Agenda

As large companies and global brands increasingly aim to meet more ambitious greenhouse gas reduction targets and net zero goals, the demands they will put on their suppliers to report and reduce greenhouse gasses will become greater. This supply chain pressure is already in evidence in certain sectors such as food, fashion and construction, and is likely to spread to all sectors and all manufacturers globally. Those manufacturing organizations that are proactively decarbonizing both their own products and are active in engaging with emissions removal programs in their own supply chain are likely to become the low carbon suppliers of choice to their customers in the new net zero world. Therefore, more research will be needed to determine which sectors and which supply chains are under most pressure to decarbonize, and how human centric manufacturing and industry 5.0 can help solve the dual problems of a lack of reliable short- and long-term usage data and a lack of strategic plans to decarbonize manufactured goods globally.

In Figure 5 the agenda for future research regarding the achievement of the Dynamic LCA is summarized along with the current information streams that are possible from many modern motor vehicles in production today. It is the opinion of the authors that the ambition for intelligent product information provision (set out in Table 6) and the dynamic LCA for intelligent products model (shown in Figure 4) can be achieved if a generic parameter set can be formed and agreed on as a set of internationally accepted standards. The outer ring shown in Figure 5 suggests the future functionalities that may be provided through intelligent products. Using the illustrative case study of vehicles as intelligent products the following research directions in terms of the Dynamic LCA are especially pertinent:

- Development of component level Edge processing to aid evaluation of use and estimated lifespan for dynamic and predictive maintenance, utilizing component embedded end of life data for reuse /remanufacturing/recycling stage

- Provision of a component level connected material inventory to aid the calculation of an overall carbon footprint of production and energy consumption/emissions at 'in use' stage of the product
- Collection and analysis of Connected Vehicle Monitoring Data utilizing a combination of Edge and cloud data repository/offline processing.

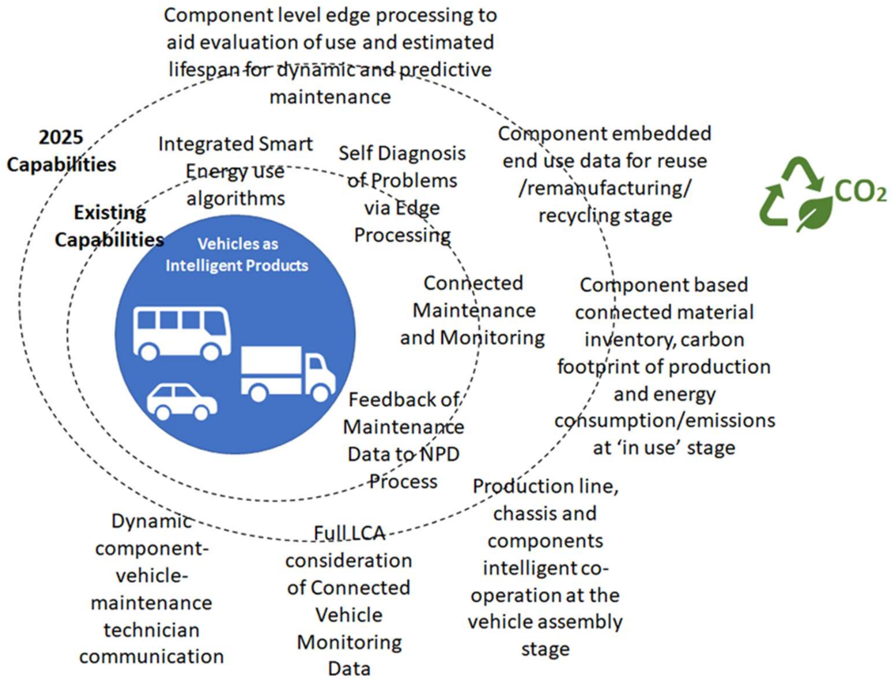

Figure 5. Future research directions prompted by the Dynamic LCA concept proposed in Figure 4.

Cobots for use in end-of-life disassembly processes may become increasingly popular as a combination of both repetitive robot and skilled human activities are required. Cobots would need to be embedded with cognitive architectures that support them in achieving this goal. Such an architecture would also include intelligence on how to address the challenges of unstructured environments and the variations found within them. These architectures would need to be supported by optimizing algorithms that adapt based on conditions in the environment. Population based algorithms such as in [98,99] that do not rely on pre-defined surrogate models could support this. Furthermore, a human in the loop approach would be assisted with the addition of parameters and information sets made possible by the dynamic LCA concept and active participation of intelligent products in their end-of-life treatments.

7. Conclusions

While the move towards Industry 4.0 has motivated a re-evaluation of how a manufacturing organization should utilize the latest in digital production automation systems a gap has emerged between performance and efficiency gains sought and actually achieved. The big data revolution coupled with Internet of Things (IoT) communication technology and the availability of low-cost miniaturized sensors has provided the potential for a new level of awareness on the current status of shop floor machine and robot operation and the establishment of a real time picture of production status available to workers and management alike. However, the knowledge and skills of workers are still required and are likely to be the missing link between promised gains and those achieved in the real world. Industry 5.0 sets a new agenda for human centric and assistive technology development and provides a shift in focus towards environmental goals.

The increasing availability of data on materials use and potential for recycling can be harnessed with the development of a new generation of products with built in sensing, processing and intelligence. Through intelligent products the realization of circular economy goals provides a compelling argument for human skills and knowledge to be combined with automation technology for the realization of ambitious recycling targets, especially in light of the increasing need to decarbonize manufacturing.

In the visualization of intelligent product material (recycling and re-use) manifests the Digital Twin concept could play a role in the presentation and interaction with this increasingly complex set of data and descriptions [100,101]. Many works exist on visualization for worker communication and there is also a strong argument for a role for extended reality and metaverse applications; viewable through headsets, Augmented Reality equipped safety goggles or even tablet devices used on the shop floor.

The role of the human in moving towards net zero production, through the increased understanding and arbitration powers over information and decisions, is paramount; this opportunity is further enabled through the use of intelligent products.

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