

Abstract: This paper provides a classification of manufacturing types in terms of new technological tools provided in the Industry 5.0 framework. The manufacturing types agile, holonic, flexible and reconfigurable benefit from and are potentially changed by Industry 4.0 technologies and the human-centric focus of Industry 5.0. Furthermore, the use of Lifecycle Analysis (LCA) provides a holistic method for estimating the true value of emissions emitted during the carrying out of manufacturing decisions. As a result, LCA may be used as a central guiding framework, in addition to the use of Circular Economy metrics, for decisions in manufacturing whose results could be presented to humans as part of a scenario-generation system using visualisations within a Digital Twin environment. This enables a decision maker to make informed decisions regarding current and future production needs. Regardless of the size of production facility, this integrated approach is perhaps the most significant gap in research identified by this survey of manufacturing types and systems when viewed through the lens of Industry 5.0. This paper makes the contribution of providing an assessment of the major manufacturing types in the context of Industry 5.0, highlighting the gaps in the current research and providing a sustainable and human-centric agenda supported by LCA use with modern production methodologies.

Keywords: human-centric manufacturing; human in the loop; Lifecycle Analysis (LCA); Internet of Things (IoT); Industry 4.0; Industry 5.0; holonic manufacturing; flexible manufacturing; reconfigurable manufacturing; agile manufacturing

1. Introduction

As manufacturing technology and processes have changed over time, their evolution has been classified into different paradigms. The shift to interconnected digital technology, based largely on Internet protocols, has been termed Industry 4.0. Covering a wider spectrum of the economy than just production systems, Industry 4.0 is seen by some authors, such as Chen [1], as taking Industry 3.0’s flexible manufacturing paradigms and pushing the flexibility further. As shown in Figure 1, since the 1950s, manufacturing processes have been developing in sophistication, providing the means to mass produce goods with increasing opportunities for customisation of products. Traditional routes to the retention of the ability to produce a variety of product types in one production location have seen notions such as the job shop recently transform from small-scale manufacturing at the SME level into multipurpose makerspaces, aided by rapid-fabrication technology and digitally controlled machines and connected supply chains. It is also the case that cellular manufacturing has developed in a similar “maker” direction, with smaller manufacturers that are able to provide highly customised products.

The automation of the flowshop has brought higher productivity and volume for mass customised production. Flexible manufacturing has focused on intercommunication...
between machines and the production line as a whole, with the capability of dynamically rerouting products between machines. Agile manufacturing utilises Just-in-Time techniques, as well as innovations in data exchange, to enable fast customer response times, while utilising modularisation in product design and postponement to enable the late assembly of product variants in response to individual customer orders.

In reconfigurable manufacturing, flexible machines are used for rapid real-time retooling between product and part variants, as well as flexibility of shop-floor layouts. Holonic manufacturing [2] presents a vision of a production system divisible into cooperating agents known as “holons”. Borrowing much from the philosophy of object-oriented software design, an individual product contains information relating to its assembly into a product and may be tracked throughout the production process, allowing for real-time dynamic routing and rerouting of such components within a production line. The latest innovations in connectivity, such as the Internet of Things and wireless connectivity with artificial intelligence, offer opportunities to provide new levels of automated control and scheduling in various manufacturing types. Smart manufacturing, also known as intelligent manufacturing, has been seen as the latest vision for mass production, with its roots in paradigms such as Industry 4.0; it is also heavily linked to the rise of personalised production and the newer Industry 5.0 vision.

![Figure 1. Evolution of manufacturing paradigm shifts [3]. (Adapted from [4] and modifications of [5]).](image)

Nevertheless, while recognising the strengths of digital manufacturing technology and the levels of intelligent automation that are possible, there has been a growing realisation in the past decade that there are limitations to the current autonomous systems. Furthermore, the growing importance of the environment has led to a reassessment of the priorities facing manufacturing in the remainder of the 21st century.

Since its inception in 2011, Industry 4.0 has been one of the leading paradigms popularising the introduction of digitally controlled production machinery, management and communication systems [6]. The use of the latest developments in computing technology and software has allowed the possibility to design, operate and maintain a factory through computer-based representations or Digital Twins of the plant. One of the main drivers behind this new reality is the availability of industrial data emanating not just from management systems but production-line machinery connected through Internet of Things (IoT) communications hardware. Artificial intelligence (AI) has provided a means to manage and process the Big Data sets and stream data produced by the entities of the manufacturing plant in near-to-real and real time. This has led to the realisation of a new level of sophistication in industrial automation solutions, especially when AI is used in the control
of production-line robots and simulation of production management systems. Despite this rise in automation in the near-to-mid future, it is still the case that manufacturing systems will require humans in the loop to provide supervisory-level mediation for even the most autonomous implementations [3].

The EU (European Union) [7] 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. The EU goes on to 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 CO₂ output, waste reduction and circular treatments for waste materials; (2) human-centric approach—human skills and both tacit and explicit knowledge are paramount and systems are designed to leverage these factors rather than replace through complete automation solutions; and (3) resilience—more robust processes and factories and more resilient supply chains.

This paper outlines the use of Lifecycle Analysis (LCA) as a methodology to dynamically communicate sustainability metrics to human decision makers at key points within the manufacturing process. Uniquely, this consideration is made in the context of the major manufacturing types and systems available to producers today, while justifying the need for human intervention over complete automation in the performance of the decision-making role.

In previous works considering Industry 4.0 and the classic manufacturing types, the field of sustainability has often been missing. This paper addresses this gap by making the case for LCA in achieving sustainability goals by leveraging human skills and knowledge (also addressing two major pillars of the Industry 5.0 paradigm). LCA provides a holistic method of estimating the true value of emissions emitted during manufacturing and at the former and the latter stages in the manufactured products lifecycle. In this work, the major manufacturing types are represented in the context of the Circular Economy with a future agenda for their reconsideration from the ground up as sustainable human-centric production process methodologies and systems. In Section 2, the methodology applied in this paper is discussed and research questions are put forward. In Section 3, an outline of Industry 4.0 is presented, followed by introductions to Industry 5.0 human-centric manufacturing, sustainability issues and the role of LCA in Section 4. In Section 5, a review of the classic manufacturing types is made, and research gaps are identified. Section 6 presents a discussion of the findings, and the paper is concluded in Section 7.

2. Methodology

In this research, a structured review was undertaken in order to derive answers to the following questions:

Research question 1: How are digital technology approaches being used with the classic major manufacturing types? In particular, how is the consideration of digital technologies popularised in these manufacturing systems with the advent and development of the Industry 4.0 paradigm and similar international programs?

Research question 2: Are human-centric approaches, a core of Industry 5.0, used in the major manufacturing types? How are humans to be kept in the loop, and what is the justification for their inclusion linked with the introduction and use of technologies that are deemed human centric (designed for human use, inclusion of knowledge from workers and enhancement of their performance and efficiency)?

Research question 3: Is there a role for the Lifecycle Analysis (LCA) in achieving net zero sustainability goals with the major manufacturing types? While it is the case that a range of methodologies and techniques have been proposed for the achievement of sustainability goals in industry, this paper explores the case of the use of LCA in the holistic monitoring and carbon emissions for net zero.

The search terms for each of the classic manufacturing types were combined using the following form: “major manufacturing type” AND “approach” (for example, “holonic manufacturing” AND “agile”). Using this keyword format for many of the manufacturing
types, over 1000 papers were returned. In order to further filter the papers, we decided to employ the “PRE/” term with a combination of 0-to-10 intervening words allowed between the searched-for terms (to ensure the two search terms were found in a contiguous fashion). In addition, we decided to focus on papers published after 2011 (the Industry 4.0 report publication date) and examine, in detail, papers from 2018 onwards. This allowed for a further stage involving the rapid analysis of abstracts, introductions and conclusions (including findings and future research) for each paper and an in-depth analysis of papers included in this review paper.

This review also considers the employment of human-centric/human-in-the-loop approaches used with the major manufacturing types. When identifying relevant papers for the initial stage, the following keyword form was used in Scopus:

(TITLE-ABS-KEY (“manufacturing type” AND manufacturing AND human AND centric)) OR (TITLE-ABS-KEY (“manufacturing type” AND manufacturing AND human AND in AND the AND loop) AND (LIMIT-TO (SUBJAREA, “ENGI”)).

Table 1 provides a summary of the papers found when the two keywords “human centric” and “human in the loop” are searched for. In Table 1, it can be seen that both smart and intelligent manufacturing techniques attracted the most research attention, along with flexible manufacturing. Agile and reconfigurable drew the least attention, though the number of papers grew beyond that shown in Table 1 when the search conditions were relaxed and the additional manual filtering was employed to identify relevant papers.

<table>
<thead>
<tr>
<th>Search Term</th>
<th>Peak Year</th>
<th>Published in 2022–2023</th>
<th>Total</th>
</tr>
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<tbody>
<tr>
<td>“Agile Manufacturing and Human Centric” OR “Human in the Loop”</td>
<td>2022</td>
<td>4</td>
<td>9</td>
</tr>
<tr>
<td>“Flexible Manufacturing and Human Centric” OR “Human in the Loop”</td>
<td>2022</td>
<td>23</td>
<td>77</td>
</tr>
<tr>
<td>“Holonic Manufacturing and Human”</td>
<td>2005</td>
<td>3</td>
<td>32</td>
</tr>
<tr>
<td>“Reconfigurable Manufacturing and Human Centric” OR “Human in the Loop”</td>
<td>2022</td>
<td>4</td>
<td>9</td>
</tr>
<tr>
<td>“Smart Manufacturing and Human Centric” OR “Human in the Loop”</td>
<td>2022</td>
<td>50</td>
<td>112</td>
</tr>
<tr>
<td>“Intelligent Manufacturing and Human Centric” OR “Human in the Loop”</td>
<td>2022</td>
<td>25</td>
<td>90</td>
</tr>
<tr>
<td>“Cell Manufacturing and Human Centric” OR “Human in the Loop”</td>
<td>2022</td>
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For “holonic manufacturing” a relaxation of the terms “major manufacturing type” AND “approach” was allowed, for categories other than holonic the relaxation brought back an increased range of often weakly related papers. Moreover, this technique was able to allow for the manual identification of additional holonic manufacturing papers implementing a “human” approach whilst not explicitly stating the keywords.

3. The Rise of Industry 4.0

The notion of digital manufacturing is a central theme of Industry 4.0 and since 2011 many authors refer to smart or intelligent manufacturing as a new type of production system [8–11]. The sophistication of sensing capabilities combined with artificial intelligence and streaming data from the production line, customers and the wider business
environment have provided the opportunity for this new type to emerge. The digital manufacturing may be seen as a Cyber–Physical System (CPS) [12–19] involving connectivity between hardware equipped with sensors and intelligent software, with the possibility for humans to be assisted in their tasks by this technology combination [20,21]. CPS may be further augmented through the concept of Intelligent Products where manufactured goods contain on board combination of sensing, processing and network connectivity so that they may relay information to manufacturers about how they are used by the customer and share data with the manufacturing process as they are being assembled [17]. It is also the case that CPS may be seen as a service-based architecture composed of discrete activities that call be called up and activated programmatically [22]. In enabling connectivity between both physical and software-based assets the functionality provided by the Internet of Things (IoT) ensures ease of connectivity and the possibility for common data exchange standards [19,23].

The notion of control in such a complex digital manufacturing system, as envisaged in Industry 4.0, requires a sophisticated mode of visualisation if human understanding and meaningful interaction are to be realised. The Digital Twin has the aim of providing a software representation of a physical system which, in some cases, be connected in real time to mirror changes in the real world as they happen, for example, on a production line [5,24–26]. Eyre et al. [27] define three modes of Digital Twin operation as follows: supervisory—where the live state of a system is displayed; interactive—in this type of Digital Twin, either a single parameter or a discrete number of parameters of a physical system are monitored and controlled by the Digital Twin; and predictive—where the state of the system is monitored over time, and AI approaches are used to predict and warn about future states so that action may be taken by either humans or automated systems acting on or integrated with the physical assets being monitored by the Digital Twin. Further concepts also pertain to the data capture and analysis capabilities made possible by the Digital Twin concept. Lee et al. [14] make the case for this data-repository possibility by describing a “time machine” type functionality that would allow the Digital Twin to be rewound to an earlier state to provide answers to problems detected in real time within the monitored system; similarly, prediction functionality could also warn of possible future states, perhaps for the purpose of dynamic maintenance scheduling.

4. Industry 5.0: Human-Centric and Sustainability Pillars

The recognition of workers and the roles they can still perform in the modern manufacturing organization has led to the proposal of Industry 5.0 being put forward as a major research strand, in addition to the notion of human-centric technology for shop-floor and supervisory roles [7]. It is also the case that Industry 5.0 seeks to rebalance the agenda towards more environmentally sustainable manufacturing solutions. The two pillars are explored in more detail within this section.

4.1. Human-Centric Manufacturing

Human-centric manufacturing or the human-in-the loop concept is seen as central to the realisation of Industry 5.0. The role of the human is seen by some as becoming more rather than less important in the age of highly automated industrial systems, according to Emmanouilidis et al. [28]. Turner et al. [29] put forward a research agenda for the realisation of the following aims: personalised production that allows consumers to co-create highly customised products with manufacturers; human-centric manufacturing, which uses technology to aid workers in collaboration with automation; and net zero carbon production and realisation of Circular Economy aims. Turner et al. [29] foresee that the route to achieving the three aims involves the combined use of Industry 4.0 technology with production methodologies for human-centric production and sustainability (Figure 2).

Digital automation systems from Industry 4.0 that have been adapted or designed to work with humans [30,31] in the form of Cyber–Physical Systems (CPSs) may provide a step change in the inclusion of humans in more efficient production scenarios rather
than their removal and replacement by machines alone. Humans are very much seen as vital components in the mediation and control of context-based decisions that are still difficult for AI to process alone, requiring the need for automation to communicate in a meaningful way with people [20,28]. The move towards the augmentation of human workers with assistive technology is an active field of research [32–35]. In an earlier move towards human-in-the-loop use of digital technology, Operator 4.0 encouraged a synergy of manual and machine skills to form human-centric Cyber–Physical Systems, designed to leverage and enhance human skills while promoting social sustainability through workplace inclusion of diversity [34,35]. The Operator 4.0 concept has been recently extended into the Operator 5.0, which is centred on enhancing the resilience of manufacturing systems through the enablement of humans to work with automation solutions [36]. Concerns about the adoption of Industry 5.0 and the process involved in this transition have led to questions about how humans will gain trust in automated systems and the possibility for a framework of ethical practice to be codified within assistive worker technologies, with a particular focus on the functioning of collaborative robotics [37,38].

The changes wrought by the latest “intelligent” digital technology are not just being felt in industry; wider society can benefit from their application. Society 5.0 is a paradigm put forward by the Japanese government to describe and promote the use of cyber–physical technology to help better address social problems and issues, while enabling environmentally sustainable economic development of the country and realisation of “conscious capitalism” through its citizens [30]. This inclusion of views of wider stakeholders in the operation of industry is seen as paramount, though frameworks for its assessment as a successful strategic goal are currently limited. One methodological approach, which was put forward by Dudek et al. [39], utilises a set of indicators to establish and formalise...
the social-responsibility position of energy companies, finding that the percentage-based metrics used lend themselves to the comparison of organisations of different sizes and geographical locations [39].

A particular step change in the nature of production that started before and during the introduction of Industry 4.0 technology is that of the move from mass customisation to that of personalised production, where manufactured goods are tailored to the individual customer’s needs [40–45]. It is also known as mass individualisation [46], and its potential for savings on material use and reduced waste and scrappage in the production process are significant. When realised as part of a wider Circular Economy program where the design of products and their full lifecycle use and end-of-life treatments are considered, personalised production can also make valuable contributions toward net zero production and sustainability goals [47,48].

4.2. Sustainability in Industry 5.0 and LCA

The concept of Industry 5.0 may also take the form of the pursuit of net zero carbon goals (as in the UK) and the implementation of a Circular Economy, which offers opportunities for the production of products with longer life spans and improved repairability/reuse options, lower levels and zero levels of pollution from manufacturing processes and products whilst they are in use. Industry 5.0 also promotes the inclusion and enhancement of human skills and knowledge within automated systems, where automation is assistive in nature rather than having the single purpose of eliminating manual tasks and labour from industry, as a route to higher productivity levels. This paradigm also seeks to address the resilience of the manufacturing industry and supply chains to world events [7].

A Lifecycle Analysis (LCA) is an assessment that considers the entire lifecycle of a given product, taking into account all the resources that are required and the pollutants that are emitted throughout all stages of its lifecycle, “from cradle to grave” [49]. The LCA is codified by the International Standard ISO14040 [50,51]. In terms of its applied use to manufactured products, a recent work by Ketkale and Simske [52] utilised the methodology to examine the production of cardboard boxes in the United States. The authors [52] found that significant reductions in carbon output can be made by considering a lower requirement for raw material in the production process for the boxes [52]. In other sectors, Roy et al. [53] reviewed LCA use in the assessment of the production of food products. LCA category simplification has been needed for its use in the construction sector, especially in application to building materials’ use [54]. The LCA methodology can also help identify unintended consequences associated with a change to different processes used in industry [55].

Turner et al. [29] put forward an LCA-based approach that utilises the sensing and communication capabilities of intelligent products to provide data on their usage. As mentioned earlier, Intelligent Products contain a combination of sensing, processing and network connectivity so that they may relay information to manufacturers about how they are used by the customer [17]. These data, when analysed, may inform maintenance actions and help in the calculation of constituent parts’ life span (maintenance actions) and the amounts of emissions produced. The LCA may also be applied to the entirety of the manufacturing processes and at the end of life of the product to help assign the correct treatment (such as the choice between repair, remanufacture or recycle options). As can be seen in Figure 3, carbon emissions may be produced at the stage of raw material extraction/processing, in manufacturing, in use and at the end of the life of a product [29].

The dynamic nature of the LCA approach put forward by [29] and shown in Figure 3 is realised by the ability for intelligent products to communicate their status in real time, allowing for an analysis to be made based on both historic and present data, perhaps in the form of a Digital Twin dashboard for LCA. The same LCA methodology could also extract data from a factory, as it operates for a holistic picture of the environmental impact of a manufacturing operation.
4.3. LCA Use in the Circular Economy

The Circular Economy (CE) is motivating industry and society to move away from the current “take, make, dispose” model of production through reuse, remanufacture or recycling of materials [56] and is now seen to be working in tandem with international efforts to achieve net zero carbon outputs. While CE concepts are rapidly becoming accepted, holistic methods to monitor, measure and mitigate such pollution outputs are still yet to be popularised within industry. The concept of Lifecycle Assessment (LCA), when used in relation to the Circular Economy, provides a methodology for the estimation of the potential environmental impacts of a given product or a service [57]. The work of Hegab 2023 [58] describes CE “resource-based product-level indicators” as including the following measures:

- Reducing production losses;
- Changing material composition;
- Using more of technical lifetime (incl. reuse);
- Remanufacturing;
- Material recycling;
- Energy recovery;
- Increasing technical lifetime by design;
- Material extraction;
- Material production;
- Component and product manufacturing;
- Use;
- End of life.

Jerome et al. [59] highlight the value of the LCA approach and note that CE alone does not address the full remit of LCA; rather, the two methodologies should be used in combination. Beemsterboer et al. [60] provides a narrative on the general simplification of LCA for different industry-based uses.

5. Review of the Classic Factory Types

In Figure 4, the distinction can be made that, while cell, lean and holonic are greater-and lesser-degree manufacturing types with distinct resource organisation methodologies, flexible, reconfigurable, agile and smart are more akin to systems composed of methodologies, process types and supporting technologies.
While makespaces are best known as “hacker” spaces, providing the incubation resources (shown in Figure 4). The following subsections detail the manufacturing types and systems. This type of manufacturing system is often used by contractor suppliers or startups/R&D

ties. While makespaces are best known as “hacker” spaces, providing the incubation resources due to the fact that the facility has to produce a variety of products. Route sheets often trigger a move to a flowshop. These manufacturing systems produce small customer-ordered bespoke batches and high-value products, with their workers often being required to demonstrate a range of skills. In addition, the equipment in job shops is often general purpose due to the fact that the facility has to produce a variety of products. Route sheets are often used to control the flow of materials through this type of manufacturing system. This type of manufacturing system is often used by contractor suppliers or startups/R&D departments before going mainstream. As the products mature and more products orders are created, the job shop evolves into a continuous mass production facility, at which stage the system becomes cumbersome. The need to build a medium-to-large volume number of products in a system that is designed initially for small batches and bespoke orders can often trigger a move to a flowshop.

It is perhaps the case that with the rise of Industry 5.0 and the Circular Economy, there is a future for the job shop in the form of makerspaces. Prendville et al. [62] provides a discussion on the makespaces concept where small-scale factory production methodologies provide local “Community-based digital fabrication workshops” capable of realising designs through to the prototype or low-scale-production stage or act as repair facilities. While makespaces are best known as “hacker” spaces, providing the incubation resources for experimental design and development of new technology, this methodology may provide the impetus to personalised production, co-creation and a new methodology for R&D in this mode of production. Pathak et al. [63] provide a compelling case for the use of makespaces in the provision of small-scale recycling workshops set up to reclaim materials from electrical-waste and repair/remanufacture consumer electronics products as part of a Circular Economy methodology involving reverse logistics.

The “Factory in a box” concept is another small-scale production concept where job shop and cell type methodologies are combined to provide a concept where production machinery comprising a manufacturing cell is installed within a shipping container size space [64].

Figure 4. Classic and modern manufacturing types and systems (adapted from Mehrabi et al. [61]).
Flowshop: The flowshop makes use of manufacturing lines with dedicated machine stations. The aim of this manufacturing line is to produce high volumes of products in an efficient and cost-effective way. As a result, specialised equipment is used, and it has a high initial cost/investment for setup. It also carries a higher risk than the job-shop variant because of the gamble that there will be enough customer orders that lead to a return on investment on the specialised equipment required. In this scenario, the skills of the human are transferred to machines performing the majority of the more strenuous tasks. The flowshop ensures that products flow through the manufacturing system, spending an allotted amount of time on each stage. The manufacturing system is arranged as a sequence of activities to be applied to a product in production. Depending on the product type, such lines could have a manual assembly line at the end or at a stage (or stages) in the process. The flowshop’s automation must not be too rigid due to the fact that some parts of a product may need to be replaced due to changes in regulations or materials and product functionalities derived though continuous improvement programmes. It was because of such needs that the concept of the flexible manufacturing system was invented.

The flexible manufacturing system (or type): This type enables in-production changes in product parts and families to be made. Flexible manufacturing systems (FMSs) make use of components such as (i) Numerical Control Machines that can be programmed with a variety of processing regimes to apply to a product; (ii) a material handling system to handle products and transport them between machine heads; (iii) work holding devices (pallets) to hold products while operations are performed on them and networks that ensure synchronised communication with sub systems and the wider production line. Flexible manufacturing as a concept was popularised as a method of achieving mass customization in medium volume production scenarios [65]. Browne et al. [66] identified eight types of flexibility: machine—ease of making changes to machines to allow for the production of different parts; process—the ability to simultaneously produce a variety of parts with each type requiring different materials; product—ability to quickly switch production to a new product type; routing—ability to reroute products around machine breakdowns; volume—profitable operation at different volumes of production; expansion—the ability to easily expand the production line, operation, and production—the type and variety of parts that may be produced. FMS has an initial high cost and also carries a risk of investment in that it is bespoke in design and often tied to a particular product variety. The initial setup time to manufacture a particular line of products is high and the design can take years to realise. Such manufacturing systems are normally supervised by a team of manufacturing personnel who work around what is often seen as an island of automation. This form of production is often seen in the light of smart manufacturing activities and paradigms in that descriptions of flexibility pertain to “intelligent” enabling technologies [67]. As with other production methodologies, the rise of personalised production is also driving the further development of flexible manufacturing systems [43]. The increasing use of Internet of Things (IoT) sensors in modern production system manufacturing scenarios is a trend also reflected in flexible manufacturing. When utilising sensor streams communicating often complex information it is advantageous to use a form of metadata to accurately tag and describe individual data points and sets. The use of Ontological systems to “read” and process such annotated data can lead to the realization of deeper insights and a reduction in misinterpretations. The work of [68] describes how such semantically described data, when used with a Webservice architecture, can provide greater interconnectivity between components of highly automated flexible manufacturing systems and assist in the successful delivery of inherent operations and scheduling tasks. Specific technologies such as RFID (Radio-Frequency Identification) tagging are seen as one specific enabling component of flexible manufacturing, with regard to scheduling of jobs [69], whereby parts are encoded with assembly instructions and ready by machines installed on automated production lines. Much flexible manufacturing research is still focussed on the optimization of production scheduling through the use of machine-learning algorithms [69–72].
The agile manufacturing system: The agile approach has been characterised by Gunasekaran [73] as the “ability of a producer of goods and services to thrive in the face of continuous change”; this system is also associated as a methodological component for the delivery of mass customization strategies. Manufacturing systems may face fast changing pressures through advances in technology, changing market tastes and increasing global interconnectivity [73]. Agile manufacturing is different from Lean production through the need for flexibility to changing market needs, and according to Gunasekaran [73] this creates a tension between the need to be flexible enough to react quickly versus the need for cost control and waste elimination from manufacturing processes. Gunasekaran [74] provide a model of the agile paradigm, identifying four central factors of this approach: quality, cost, flexibility, and responsiveness. Four axes of development pertaining to agile are also identified in [74] as: (i) strategic planning; (ii) product design; (iii) virtual enterprise; (iv) automation and Information Technology (IT). In their methodology for agile Implementation [75] cite a number of actions a manufacturer may consider as a result of considering this practice, including: the need to reduce time to market for new products; implementation of Just-in-time (JIT) practices; adherence to new environmental standards; industrial and business process reengineering. Agile manufacturing requires manufacturers to access resources beyond their current ownership, meaning that producers must work more closely together with suppliers and sometimes competitors [76]. At a similar time of inception to the concept of agile came that of the Virtual Enterprise [77]. The Virtual Enterprise is a concept where technologies such as Electronic Data Interchange (EDI) allow for organisations to digitally interact with each other remotely, ultimately allowing functional level interactions to be performed between companies (individual firms are no longer islands) [77]. The utilisation of knowledge management as a practice, and that of the knowledge worker, are both key factors [74] utilised by agile in the promotion of the “Learning Organization”. A framework for the implementation of agile within an organization has been put forward by [78] that provides three generic strategies: responsive—flexibility and responsiveness to changes; quick—customer focus and fast to market with products; and proactive—full customer focus and fast to market, with flexibility and responsiveness.

In their work, Houyou et al. [79] introduce the concept of the IoT (Internet of Things) as an enabler for a more agile manufacturing organisation, envisaging an automated production system incorporating networked intelligence and context awareness. Cheng et al. [80] examine the use of IoT enabled networks to match manufacturing resources supply and demand signals; leveraging the concept of servitization in manufacturing, these authors propose that such networks are utilised to digitally compose new collaborations between manufacturing organizations and their supply chains. The enablement of IoT data exchange by Industry 4.0 recognised standards such as OPC UA (Open Platform Communications Unified Architecture) is investigated by [81] in relation to agile manufacturing. The author [77] put forward the potential for agile goals to be met in a fully networked manufacturing environment and raise the notion that the traditional Automation Pyramid may be flattened in form with the roles of ERP (Enterprise Resources Planning) and MES (Manufacturing Execution System) systems being challenged or redefined. Rauch et al. [82] highlight the possibility to reimagine manufacturing in a distributed form, where geographically dispersed mini factories are connected by network technologies to provide agile production facilities capable of localised production, taking advantage of short (and more environmentally sustainable) supply chains. The notion of socialization as a success factor in advanced manufacturing systems is the subject of work by Tao et al. [83], who popularise the need for customer participation on the development and sale of new products. Agile is gaining attention in the delivery of mass personalisation systems within manufacturing, it is the argument of [83] that in delivering highly personalised products (or in serving the market of one [43]) closer involvement of the customer base is required. It is the opinion of Potdar et al. [84] that no generic strategy or implementation of agile has been attempted, with most efforts concentrating on individual company cases or industry sectors.
Reconfigurable manufacturing system: In order to produce parts that are liable to changes in functionality and structure, within a particular part family, reconfigurable manufacturing systems were introduced to allow for such fast adjustments in production to unforeseen needs and new product variant demands and differ from flexible systems that are most commonly limited to the production of planned variant ranges only [65]. With the original concept put forward by [85] reconfigurable manufacturing is defined by the following six characteristics: customization—flexibility relating to the ability to produce a product family; convertibility—ease of conversion of existing machines for new production scenarios; scalability—ability to change capacity for new production volumes; modularity—the scope for functional division of manufacturing into discrete units; integrability—ease of manufacturing modules interfacing with each other; and diagnosability—automatic identification of root cause of problems within the system [86].

One of the early challenges for reconfigurable manufacturing was that of the ramping up of production with sufficient speed, an issue addressed in [61] by introducing a dynamic model to address scale up issues. The work of Wang et al. [87] addresses issues of layout optimisation by using machine-learning techniques drawn from the field of evolutionary computing. The subject of optimization is also explored by Yelles-Chaouche et al. [88], who provide a survey of algorithmic approaches applied to reconfigurable manufacturing. The challenge of scheduling production within a reconfigurable system is addressed by Azab and Naderi [89], with a focus on exploring the complexities and timings required to switch production between different product families. Maganha et al. [90] state that the design of a flexible manufacturing implementation should be seen as a cyclical process that evolves over time rather than a one-off activity. The need for virtual representations of reconfigurable manufacturing systems was made by [72], who introduced the concept of a digital avatar to represent a manufacturing layout detailing individual production machines. As with other manufacturing methodologies, the rise of personalised production is a further stimulus for research into reconfigurability, along with the potential of digital technologies [91–94]. For some authors, it is still an open question as to how Industry 4.0 technologies will influence the future development of reconfigurable manufacturing systems [95].

Holonic manufacturing system (or type): Holonic manufacturing [2] presents a vision of a production system divisible into cooperating agents known as “holons”. The work of [2] defines three types of holons based on the concept of object orientation: order holons, product holons and resource holons. In the holonic manufacturing system, programs relating to the manufacture of products are held in the product components themselves. As a result, a shift of emphasis is made in that products are determining their manufacturing process rather than machines or the production line. In effect, products are units of information, embedding both machine operations and routing sequence, that are worked on in sequence towards their completion. However, the routing sequence would vary from one variety of product to another variety of product. Research into routing sequences required for different products to efficiently navigate the manufacturing system is an active area for consideration. In [96], the role of machine-learning techniques in the selection of routes for particular products is set out utilising the notion of the ant colony algorithm and holons as computational agents. Much of the recent exploration of this manufacturing methodology considers the use of machine learning and Industry 4.0 technology [97], with the case made in [96] that the traditional CIM (Computer-Integrated Manufacturing) pyramid view of manufacturing has broken down and may be replaced with the network-technology-based distributed and delayered model nearer to that seen in other digital systems employed in service sector organisations. A consideration of Edge processing of sensor data in an IoT (Internet of Things) and cloud-enabled environment is provided in [98], research that is pertinent to the realisation of holonic manufacturing control systems. In [97], further discourse is provided on the challenges and potential of Big Data integration and use in holonic manufacturing systems. Intelligent products equipped with sensing, processing and wireless connectivity capabilities may be active participants in holonic
manufacturing. An Intelligent product is able to “monitor, assess and reason about its current or future state and, if necessary, influence its destiny” [99,100]. Ref. [29] provides an additional narrative on the use of Intelligent products and the types of parameters they may sense and process.

The complexity of product routing possible within holonic systems has led to research focusing on the use of predictive algorithms for coordination, with further use and development of the ant-colony and agent-based approach [101,102]. The use of semantic approaches, utilising specific ontologies as a knowledgebase that agents may make use of, in decision making situations for dynamic scheduling was explored by [103]. Such use of ontology has also been employed directly with the holonic methodology by [104] in the integration of supply chain organisations. In [105], consideration of the holonic approach and its potential for use in a Digital Twin context is made. It is the case that, for some authors, the automation potential possible with holonic systems can be further enhanced with the integration of human knowledge and decision-making capabilities. In [21], human-in-the-loop and so-called socially connected manufacturing systems are considered in the context of holonic-agent-based manufacturing control, along with further consideration of worker-integration strategies [106]. More diverse uses of holonic manufacturing can be found in works such as [107], which considers the application of this methodology in the construction industry and [108] where Automated Guided Vehicle (AGV) use and scheduling for warehousing picking is discussed; and [109], which involves research focused on the use of Cobot and worker interactions. Ávila-Gutiérrez et al. [110] considered the use of the holonic paradigm in the context of sustainability and circular business models. In this work, a consideration is given to the use of lean methodology within a holonic framework for the achievement of whole Lifecycle Assessment and mitigation of environmental factors relating to a manufacturing organisation.

**Linked-cell manufacturing system:** The reconfigurable manufacturing system bears some similarities to the linked-cell manufacturing system that is designed for the flexibility of being able to react to changes in customer demands and changes in designs and cater to varying product mixes. With such a system, the machines are arranged in cells joined together by a transport system that transfers the product from cell to cell. This system has also been considered in combination with flexible manufacturing technology [111] to create the flexible manufacturing cell. Kruger et al. [112] provide an interesting work that considers cell manufacture in combination with holonic manufacturing and reconfigurable production. Both the linked cell and reconfigurable manufacturing systems may, of course, be used in the achievement of or in combination with agile, holonic and flexible manufacturing types.

**Smart/intelligent manufacturing system:** In their definition of smart manufacturing the SMLC (Smart Manufacturing Leadership Coalition) identify six technologies that may enable smart manufacturing: Networked Sensors; Data interoperability; Multi-scale dynamic modelling and simulation; intelligent automation, scalable and multilevel cyber security [113]. Smart manufacturing is said by Kusiak [9] to encompass “cyber-physical systems, IoT (Internet of Things), cloud computing, service-oriented computing, artificial intelligence and data science”. Kusiak [9] go onto define six pillars of smart manufacturing: manufacturing technology and processes—the emergence of new more integrated manufacturing processes; materials—new material types including biomaterials; data—leveraging the increased production and consumption of data by digitally controlled production machines; predictive engineering—accurately forecasting the reliability of machines and intelligently scheduled maintenance windows; sustainability—a recognition of the environmental impact of manufacturing with work towards mitigation; and resource sharing and networking—the increasing interconnectedness of production, allowing distributed and remote production offered as a digitally connected service. In this direction, Yan et al. [114] propose a deep-learning approach to enable a network of factories to work together through a distributable setup for production machines, allowing coordinated production across multiple production facilities. For some authors, the term “intelligent
manufacturing” can be used interchangeably with that of smart, though Wang et al. [115] disagree, stating that smart manufacturing tends to be connected with Industry 4.0 and Big Data research, whereas intelligent manufacturing is realised through artificial intelligence, agent-based technology and optimisation methods; though this author cedes that both terms may converge when an examination of the constituent technologies is made when implementing digitisation projects in the future. Li and Si [116] describe the use of intelligent manufacturing to address one of the major challenges, the nature of production as a multiscale set of requirements for differing batches and product types required for a modern factory. Marques et al. [117] describe a number of barriers to digitalisation within manufacturing, citing the following among the factors identified: lack of interoperability or standards, security concerns, legacy equipment, lack of skilled workers and uncertain return on investment. When taking on Industry 4.0 digitalisation projects, it can be seen that, of the factors identified by Marques et al. [117], the need for standards and workforce training would require the greatest effort to address. For Yao et al. [118], the use of artificial intelligence is key to the realisation of smart manufacturing; this author also recognises the need for such intelligence within smart manufacturing in order to deliver highly customised products, even in batch sizes of one. The recognition and prominence of social data, in the form of tacit knowledge, is a valuable resource which may feed into automated systems [118], though it is still the case that humans must play a pivotal decision-making role, even when much of their discourse and actions can be captured and codified for analysis. Big Data and their generation by modern production systems are key enablers of smart manufacturing; their analysis through analytics tools and artificial intelligence can lead to an improved competitive position for the adopting organisation [8]. In enabling the human to monitor, understand and control production in a smart manufacturing system, a Digital Twin may provide a holistic visualisation and scenario-generation platform allowing a level of flexibility, data-processing capability and interactivity beyond the traditional individual machine control and management dashboards.

The Digital Twin concept has been explored by Lu et al. [5], who provide a reference model composed at a high level of three major components: (1) a model that describes physical objects in abstract form; (2) components to provide a mode of bidirectional communication between a Digital Twin and its mirrored object; and (3) an analytics and processing component to fuse data from heterogeneous sources to construct a live representation of a physical object. Lu et al. [5] also note that the development of a unified ISO standard for Digital Twins may help in the uptake and further development of this technology. Lee et al. [14] view the Digital Twin as a way of providing a manufacturing “time machine” that is capable of being wound back to see how an activity or process was performed in the past and then redesigning or optimising it based on recorded evidence and real-time performance of the physical twin. However, Tao et al. [24] point out that while there has been a focus on the capture of data from the physical world by smart manufacturing systems, relatively few research works examine the capture of data from virtual models provided by Digital Twins and scenario generation applications such as Discrete Event Simulation [3].

If realised, a smart manufacturing ontology could provide the basis of machine/human communication and collaborative human-centric production technology, especially when combined with XAI (Explainable Artificial Intelligence) algorithms. XAI aims to provide AI algorithms with narrative functionality with the capability to communicate the major steps taken in arriving at a solution to a human [3]. In bridging the gap between machines and humans, the use of XAI with ontology and semantic descriptions could help leverage the best of both worlds to provide a new level of agility to cyber-assisted manufacturing production.

Zhong et al. [10] defines a number of pertinent research directions for smart or intelligent manufacturing: smart design—combined use of VR, CAD models and 3D printing; smart machines—providing manufacturing functionality as a digitally delivered service; smart monitoring—real-time picture of machine health and operation; smart
control—cloud-based remote control of production machines; and smart scheduling—realisation of real-time job scheduling. Following on from Zhong et al. [10], of most interest in terms of future research in smart manufacturing is perhaps the mass personalisation challenge, involving the dynamic scheduling and rescheduling of production batches from size of one upwards, along with the ability to dynamically design and then produce a bespoke product at a profitable price point [43]. Tao et al. [8,24] highlight the opportunity for social integration with smart manufacturing systems, with challenges then posed regarding capturing, codifying and acting on human input in a timely and context-relevant way. While this imposes a steep learning curve for AI-enabled automation solutions, the retention of human involvement may prove pivotal. In this light, the Industry 5.0 paradigm holds promise in the form of the development of human-centric technology that is capable of enhancing human skills and complex decision-making ability while automating the more mundane activities. Kumar and Lee [119] find the following task types that may be enhanced through the use of human–machine interfaces: monitoring tasks, controlling tasks, assembling tasks, scheduling of machines, scheduling of workforce and operations, maintenance and repair tasks, and administrative tasks. Lu et al. [5] make the point that a central component of the Digital Twin could and indeed should be the human, making the case that workers are still not considered as the focal point of decision-making in smart manufacturing systems. While smart manufacturing is defined as a system, it can be used in combination with many of the more layout specific methodologies such as flexible, holonic and reconfigurable, it is arguable that those types and systems not just benefit from smart manufacturing they are actually enabled by it. Although this system is one of the most recent put forward, it is still the case that sustainability is seen as an additional component rather than an integrated holistic methodology covering every lifecycle stage of production.

**Research Gaps**

In Table 2, a state-of-the-art research summary regarding the major manufacturing types and the technology which may be employed in their operation is provided. Table 2 displays pertinent papers regarding the technology types IoT, semantic/ontology, simulation, Cobot/robot automation, deep learning, Digital Twin, other machine-learning and the human-in-the-loop/human-centric approaches that are identified for the manufacturing types agile, flexible, holonic, reconfigurable, smart/intelligent and cell.

From this review, it is very much the case that modern manufacturing approaches often utilise a combination of types for a given production challenge. Popular combinations include flexible and reconfigurable manufacturing and smart/intelligent manufacturing with flexible manufacturing. For smaller production facilities, digital technology can still have a role, such as with Liu et al.’s [120] Cyber–Physical System use with the job shop manufacturing type; an additional narrative on digital technology use with SME manufacturers is provided by McFarlane et al. [121].
Table 2. Summary of state-of-the-art research regarding the major manufacturing types.

<table>
<thead>
<tr>
<th>Manufacturing Type or System</th>
<th>Agile Type</th>
<th>Flexible System</th>
<th>Holonic Type</th>
<th>Reconfigurable System</th>
<th>Smart/Intelligent System</th>
<th>Cell Type</th>
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Table 2. Cont.

<table>
<thead>
<tr>
<th>Manufacturing Type or System</th>
<th>Agile Type</th>
<th>Flexible System</th>
<th>Holonic Type</th>
<th>Reconfigurable System</th>
<th>Smart/Intelligent System</th>
<th>Cell Type</th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>Cardin et al., 2018 [180]</td>
<td>Naticchia et al., 2019 [107]</td>
<td>Koren et al., 2018 [40]</td>
<td>Sgarbossa et al., 2020 [182]</td>
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In Table 3, the research gaps are displayed in the use of technology types and the realisation of human-centric technology for the manufacturing systems and types. The colour coding in Table 3 indicates the following: red—limited or no research is present for a topic for a given manufacturing type; amber—research is in progress; and green—many works exist for the topic and manufacturing type combination. Most notably, while the agile system seems to lack research connected with the latest digital technologies (such as Cobot usage, semantic technology, deep learning, and Digital Twin implementations), this may be due to the case that much of the learning of agile has been subsumed into flexible and reconfigurable systems. In turn, smart/intelligent manufacturing systems attract the most research attention involving digital manufacturing technology and human-centric approaches. Holonic manufacturing receives only limited attention in terms of Digital Twin and deep learning, in particular, though the case for its use in human-centric systems is made by some authors. It is interesting to note that the works are limited in the area of net zero carbon and digital manufacturing and methodologies for its summation and mitigation. This is especially true regarding the use of Digital Twin and its use for the Lifecycle Analysis. Papers also exist that contain a crossover between the manufacturing types and/or describe a combination of approaches. This is most prevalent for the smart/intelligent manufacturing system. One final gap for all manufacturing types is the limited research into sustainability and environmental issues pertaining to individual manufacturing types and systems; the majority of the current research is still at a more generic level of indicator and metric development for broad application in industry or specific sectors, with limited application and utilisation by specific production methodologies. This, perhaps, leaves open the potential for existing and new manufacturing types to be re-thought from the “ground up” as sustainable and human integrative systems.

<table>
<thead>
<tr>
<th>Simulation</th>
<th>Agile Type</th>
<th>Flexible System</th>
<th>Holonic Type</th>
<th>Reconfigurable</th>
<th>Smart/Intelligent</th>
<th>Cell</th>
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<tr>
<td>Digital Twin</td>
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<td>IoT</td>
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<tr>
<td>Edge computing</td>
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<tr>
<td>Semantic/ontology</td>
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<tr>
<td>Robot automation</td>
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<tr>
<td>Cobot automation</td>
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<tr>
<td>Deep learning</td>
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<tr>
<td>Other Machine Learning</td>
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<td></td>
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<tr>
<td>Human in the loop/human centric</td>
<td>Limited/no research</td>
<td>Research in progress</td>
<td>Advanced/mature research area</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Key</td>
<td>Limited/no research</td>
<td>Research in progress</td>
<td>Advanced/mature research area</td>
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6. Discussion

Modern manufacturing is underpinned by Lean (waste reduction) methodology, along with agile and its affordance of postponement in the achievement of profitable mass customisation. It is said by Elkins et al. [188] that “Agile systems are preferable when the demand volume for each model is relatively low and the life span of the product is comparatively short”. The use of a more “flexible” systems and types can enable the production of a greater range of products at increased volumes. It is put by this research that human-centric approaches to manufacturing are not just possible with each of the manufacturing types and systems, but they are a vital component in the volume delivery of highly customised and even personalised products, whilst minimising the environmental impact of their production. It is essential that manufacturers identify where human workers can best provide skill and knowledge inputs aided by the latest digital technologies. Automation, over recent, decades has provided many step changes in our ability to provide for an
increasing global population and market for manufactured goods. However, it is still the case that the “lights out” factory, where production is autonomous, remains out of reach for most production needs. Figure 5 shows the possibility for manufacturing to evolve to use workers in factories designed for human-centric participation and support and for humans to still have a mediating role in highly automated and autonomous production facilities in the coming years.

![Figure 5. The evolution of manufacturing, from automated to human-centric and -mediated processes.](image)

For one particular consideration, the need for humans to be retained in the loop is emphasised by the increasing need to take a holistic view of manufacturing in terms of its contribution to carbon emissions and usage of natural resources taken from the environment. The LCA methodology requires data on carbon emissions at each stage of manufacturing which are provided, in part, by sensors at factories and within logistics to provide cumulative real-time and compiled historic data for carbon emissions and for the prediction of future likely emissions. This requirement, coupled with the possibility of providing a holistic lifecycle view of manufacturing via a dashboard or Digital Twin for net carbon zero, would allow all interested parties to obtain a real-time view of carbon emissions at each stage of production and view the likely life-span emissions value of the products produced. Table 4 provides an indication of the likely users of carbon emissions information and the information types that they are most likely to require. The LCA displayed in the form of a dashboard or Digital Twin for carbon zero would provide a holistic picture of emissions and act as a platform for the prediction of future emissions and the generation of carbon-reduction scenarios. It is the role of this platform to inform all users of the emissions position of the manufacturer and related partners and to provide a Lifecycle Assessment for each of the products produced that is available and updatable throughout the goods’ life span. The traceability of materials and manufacture can also be ensured by using such a system, along with embedded marking or recording of a product’s composition. It is by providing all users with an accurate and dynamic picture of emissions that active participation in net-zero goals may be achieved. Moreover, carbon reduction should be the priority of all workers involved and will require the skills and often tacit knowledge of employees beyond corporate departments tasked with the maintenance of sustainability programs.

In addition, a number of key decision points can be identified within a manufacturing system or type relating to LCA and net zero emissions considerations requiring human input. These points are illustrated in Figure 6 for five of the major manufacturing types and systems.
Table 4. Usage of LCA carbon emissions data for different stages of manufacturing.

<table>
<thead>
<tr>
<th></th>
<th>Materials Input</th>
<th>Manufacturing</th>
<th>Supply Chain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supply-chain manager/worker need</td>
<td>View of embodied carbon for raw materials and components to be transported; predicted emissions of required logistics</td>
<td>View of embodied carbon for completed products; predicted emissions of required logistics</td>
<td>Holistic view of emissions logistics and prediction of future logistics emissions</td>
</tr>
<tr>
<td>Raw-materials/component manufacturer</td>
<td>Carbon content of raw materials and their extraction/processing or embedded carbon and manufacturing process emissions of components to be supplied</td>
<td>Carbon emissions prediction of component manufacture/raw materials processing</td>
<td>View of emissions of inbound logistics and prediction of outbound logistics emissions</td>
</tr>
<tr>
<td>Manufacturing-manager/supervisor need</td>
<td>View of emissions for raw materials and components before further manufacture</td>
<td>Holistic view of emissions of entire manufacturing operation and predicted emissions of future production scenarios</td>
<td>View of emissions of inbound logistics and prediction of outbound logistics emissions</td>
</tr>
<tr>
<td>Production-line-worker need</td>
<td>Holistic dashboard access to emissions for raw materials and components</td>
<td>Emissions of manufacturing process and predicted emissions of production choices in the remit of line operatives</td>
<td>Holistic dashboard access to emissions for inbound logistics</td>
</tr>
<tr>
<td>NPD/product-designer need</td>
<td>Carbon content and emissions of components to be used or materials required</td>
<td>Predicted carbon emissions for manufacturing process required</td>
<td>Logistics emissions view for components and raw materials transport and outbound logistics completed product carbon emissions forecast</td>
</tr>
<tr>
<td>Consumer need</td>
<td>Holistic view of embodied carbon; carbon emissions in terms of materials extraction/processing and components production</td>
<td>Holistic view of embodied carbon; carbon emissions for production</td>
<td>Holistic view of embodied carbon; carbon emissions from logistics</td>
</tr>
<tr>
<td>Repair/recycling/remanufacturing-agent need</td>
<td>Materials inventory of end-of-life products or recycling, product maintenance history carbon emissions for remanufacturing and repair (influencing repair/remanufacture/repair decision)</td>
<td>Emissions at manufacturing stage and remanufacturing and repair emissions</td>
<td>Logistics carbon emissions for returned products at the end of life</td>
</tr>
</tbody>
</table>

In Figure 6, for agile manufacturing, a production decision point often occurs at the postponement stage, where the organization will decide to what level a product is pre-built before final customization, and involving LCA and CE measures within the decision though the generation of alternative scenarios may help identify reduced carbon emission options. Providing the human decision maker with scenarios, through data analysis and artificial intelligence, heightens the probability of the selection of an effective trade-off between production output and emissions. Similarly, for flexible manufacturing, production scheduling options may be annotated with their predicted carbon values and required product volume/batch sizes (Figure 6). Where smart/intelligent factories are distributed into smaller regional units, the decision for their optimal use needs to include carbon emission values in the calculation. It is also the case that sustainability considerations
will affect the decision of when to use additive manufacturing approaches over currently cheaper traditional methods. In many cases, a Digital Twin provided at the enterprise level can provide a visual representation of the decision points so that humans may make the decision of how to balance all production choices (in a trade-off fashion) in order to best meet net zero considerations, while maintaining the ability to react to changing market conditions. Digital Twins could also be used to support the development of Human–Robot Collaboration strategies, as well as multi-agents in holonic manufacturing systems, while supported by optimisation algorithms [189,190].

7. Conclusions

It is the case today that the classic forms of manufacturing, through the deployment of digital technology, are still relevant for use in modern production environments. Even with job shop, there is an opportunity to enable small-scale localised production though the employment of technology innovations, as demonstrated by the makespaces or small-scale production facility when combined with the cell layout. Flexible and reconfigurable manufacturing approaches can also be enhanced by the integration of intelligent systems, allowing for the potential of the factory as a Web-connected service and fast turnaround manufacturing of highly customised, even personalised, products. Agility, though attracting slightly less attention as a methodology in isolation, is also a guiding force behind the move to personalised production in the age of IoT-connected machines and distributed lo-
calised production. Holonic manufacturing, although closely related in conceptual makeup to object-oriented software-engineering principles, still has to gain traction in industry as a well-known type.

It is perhaps the smart/intelligent manufacturing system that may provide the overarching framework for the operation of manufacturing types and systems in the future. While acknowledging the role of artificial intelligence is playing and will play in the future of automation solutions for production, it is important to value the changing role human workers will have in this environment. It is the case that in the pursuit of greater personalisation of production, productivity gains and adherence to sustainability goals such as net zero carbon human input will be pivotal. The tacit knowledge and problem-solving skills of human workers will increase in value when actively used in combination with automation solutions in the short-to-medium term, rather than a reliance on the implementation of purely autonomous solutions to often complex multidisciplinary decision spaces where no correct solution exists and qualitative/quantitative trade-offs must be made.

While reviewing the state-of-the-art in Industry 5.0 and its application to the major manufacturing types, we found that there is a lack of a framework for the realisation of sustainability-related decision-making in industry and the leveraging of human skills through AI in new automation solutions for manufacturing. In future research, the authors will seek to propose a wider approach for automated scenario generation and decision support for environmental decision-making in the implementation of new manufacturing solutions and their day-to-day operation. While this study considered the two central pillars of human centricity and sustainability, the third pillar, i.e., resilience, has not been explicitly included in the remit. Future work by the authors will further investigate the relationship between this third pillar and the first two and explore synergies for the realisation of systems to support dynamic and proactive responses to changes in the demands made on manufacturing processes in the future.

It is in the pursuit of sustainability goals that the premiums on human knowledge and decision-making abilities are paramount. The joint harnessing of both human talent and automation is required for the deployment and operation of new manufacturing solutions in short order if real changes are to be made regarding the way that industry operates. The use of the Lifecycle Analysis (LCA) provides a holistic method of realising the true emissions from manufacturing decisions and full life consideration of products from cradle to grave; indeed, ideally, this should be from cradle to cradle, with products being repaired and remanufactured at the end of life rather than recycled or simply disposed of. Sustainability cannot be thought of as an add-on or optional extra; instead, it must be a guiding principle in the implementation and operation of any selected method of manufacture. This paper outlined the LCA as a central guiding framework for decisions in manufacturing and how it may be expressed to human workers as part of scenario-generation systems within Digital Twin data-visualisation environments. Regardless of the size of the production facility, this integrated approach is perhaps the most significant gap in research identified by this survey of manufacturing types and systems.

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