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Cognitive manufacturing: definition and current trends

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Abstract
Manufacturing systems have recently witnessed a shift from the widely adopted automated systems seen throughout industry. The evolution of Industry 4.0 or Smart Manufacturing has led to the introduction of more autonomous systems focused on fault tolerant and customized production. These systems are required to utilize multimodal data such as machine status, sensory data, and domain knowledge for complex decision making processes. This level of intelligence can allow manufacturing systems to keep up with the ever-changing markets and intricate supply chain. Current manufacturing lines lack these capabilities and fall short of utilizing all generated data. This paper delves into the literature aiming at achieving this level of complexity. Firstly, it introduces cognitive manufacturing as a distinct research domain and proposes a definition by drawing upon various preexisting themes. Secondly, it outlines the capabilities brought forth by cognitive manufacturing, accompanied by an exploration of the associated trends and technologies. This contributes to establishing the foundation for future research in this promising field.

Keywords Cognitive Manufacturing · Reaction · Perception · Decision Making · Multimodal Data

Introduction

Since the inception of the first industrial revolution, the overarching goal in manufacturing has been to elevate productivity (Nain et al., 2022). Successive waves of industrialization have relentlessly pursued innovations aimed at delivering better, faster and more affordable products (Bradu et al., 2022; Nain et al., 2022). Modern industrial production stands at a crossroads, driven by a dynamic marketplace that increasingly demands smaller and more customized products (Bradu et al., 2022; Ji et al., 2022). Amidst these challenges, there is a compelling push for the industry to transition from traditional manufacturing paradigms to smart manufacturing (A. A. Malik, 2022).

These traditional manufacturing approaches have limited efficiency in producing customized, small-lot products and often function in silos, lacking integration across production systems, product lifecycles, and intercompany value chain (Bommasani et al., 2021; C. Liu et al., 2022; A. A. Malik, 2022). This disconnection between actual processes and their virtual representations leads to operational inefficiencies (Zheng et al., 2018). In seeking alternatives, smart manufacturing, or Industry 4.0 as it was introduced by Germany in 2011, emerges as a promising avenue (Thoben et al., 2017). The aspirational promise of Industry 4.0 is to deliver batch size one, personalized products with the economies of scale of mass production. This modern solution is characterized by its multi-agent system approach that emphasizes autonomy, heterogeneity, and decentralization (Li et al., 2022). Through this system, an abundance of data enables machines, materials, and humans to interconnect via industrial wireless networks, powered by advancements in

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Artificial Intelligence (AI), Internet of Things (IoT), and cloud computing (Ji et al., 2022; C. Li et al., 2022).

Smart manufacturing not only integrates the physical and digital worlds but also allows for flexible, reconfigurable, and adaptive production (Elahi & Tokaldany, 2020; A. A. Malik, 2022; Yousif et al., 2024). Such an environment thrives on robust data collection and utilizes this data to extract actionable insights. These insights inform predictive interventions, which continually evolve, ultimately aiming to facilitate autonomous decision making (Paasche & Groppe, 2022). Only by computerizing and digitalizing every component can a dynamic environment be fostered where each component communicates, understands, and augments the capabilities of another (Sahoo & Lo, 2022).

This progression exemplifies the transformation from a digitally enabled environment to a truly smart manufacturing paradigm. However, smart manufacturing is not without its limitations. Despite its merits, smart manufacturing primarily focuses on process optimization and predictive interventions (Mo et al., 2023; Pereira et al., 2019), to-date failing to fully address the complexity of autonomous decision making and self-learning (Zheng et al., 2018). Thus, cognitive manufacturing has emerged as the next evolutionary step in smart manufacturing which integrates a more intricate mesh of cognitive abilities. This new frontier incorporates advanced technologies like AI, big data analytics, and cognitive computing to create systems capable of complex decision making without human intervention. Cognitive manufacturing aims for a comprehensive understanding, facilitating not just the "what" but also the "why" behind manufacturing processes. With the pace of technological innovation never slowing, staying abreast of current trends is no longer optional but essential for manufacturers, policymakers, and researchers alike (Thoben et al., 2017).

Manufacturing systems have witnessed multiple phases throughout history. The relationships between each industrial revolution, the driving factors for each revolution and adopted terminologies for manufacturing systems were highlighted in (Singh et al., 2019). Whereas the first industrial revolution focused only on cost, the following eras introduced factors such as quality, time, and flexibility. The third industrial revolution also introduced terminologies such as Computer Integrated Manufacturing, Intelligent Manufacturing, and Cyber Physical Production Systems. Each system exemplifies one step further to reach the future objective of Cognitive Manufacturing.

Cognitive manufacturing has emerged as the next evolutionary step within smart manufacturing. Cognitive manufacturing caters to the industry's growing need for systems that are not just reactive but proactive, not just efficient but intelligent. This literature review aims to combine the existing research on cognitive manufacturing into a comprehensive resource, motivated by its increasing popularity as evident by the recent increase in publications and citations within the Web of Science (WoS) database, chosen for its high quality catalogue, as shown in Fig. 1, a sentiment also expressed in (ElMaraghy & ElMaraghy, 2022).

This review offers an exhaustive framework for conceptualizing the paradigm of cognitive manufacturing. Section two outlines the methodological approach, elaborating on the rigorous literature review process employed to source relevant academic contributions, and the steps taken to select the works chosen within this review. Section three seeks to establish a unified and holistic definition for cognitive manufacturing. This section aims to also spotlight its prevailing capabilities. In doing so, this review aims to encapsulate both historical developments and emergent trends, offering a holistic view of the field. Sections four to six expand on the derived capabilities by deducing the current research trends within each. Section seven presents an overview of the deduced trends and current industry solutions focusing on cognitive manufacturing and section eight provides some concluding remarks.

By adopting this structured approach, this paper aims to serve as an early conceptual framework to the new cognitive manufacturing paradigm and uncover the emerging trends within.

Methodology

This literature review aims at accomplishing two main objectives:

- **Objective 1:** Establishing a holistic definition for Cognitive Manufacturing.
- **Objective 2**: Highlighting the current research trends and deduce future trends within the Cognitive Manufacturing field.

Objective 1

To achieve this, a systemized process of collection was undertaken as shown in Fig. 2. In this full article, two sets of articles had to be collected across two different phases of investigation. The first phase of investigation gathered articles that were analyzed to define cognitive manufacturing. As preliminary discovery, the terms "cognitive" and "manufacturing" were used to select articles. However, such search returned wayward responses with articles unrelated to the topic of this review. As such a more specific search term had to be adopted. The search was conducted using ("cogn*" AND "manuf*") as the title search term to retrieve papers that include any derivative of cognitive and manufacturing in their title. As shown in Fig. 3 that search returned 70 papers which were

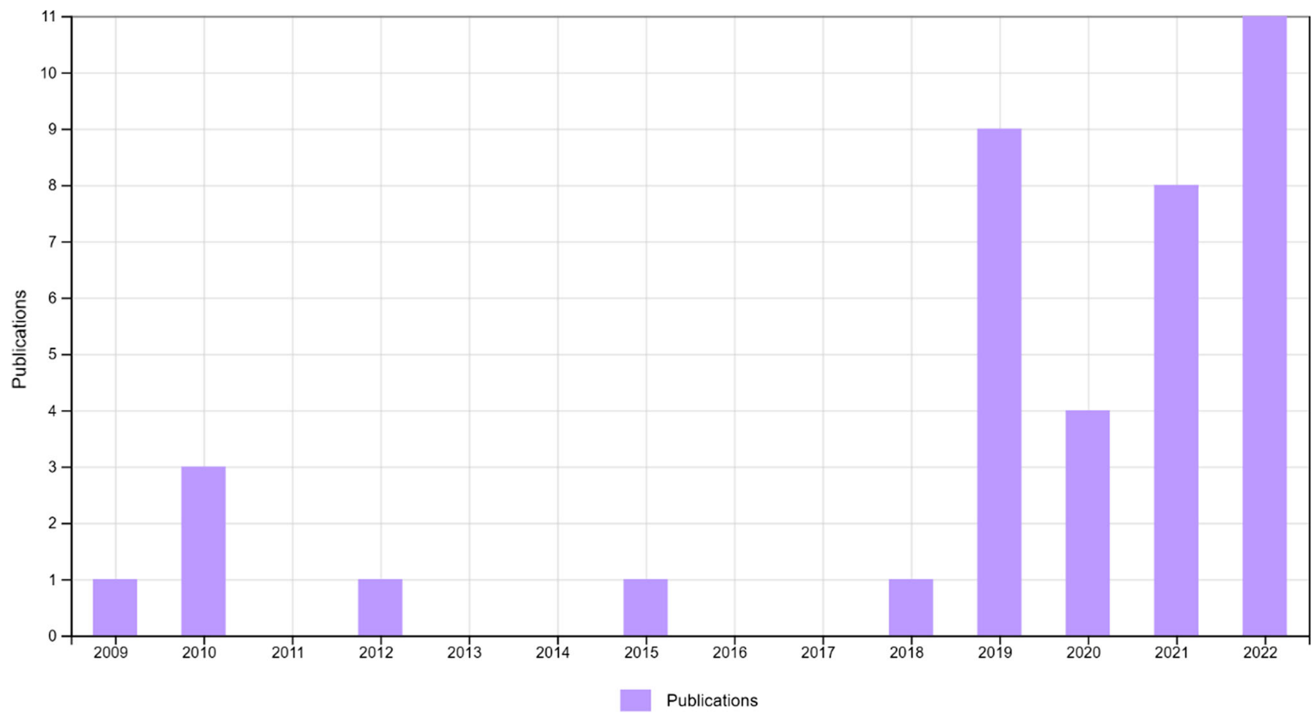

Fig. 1 Number of published works about cognitive manufacturing

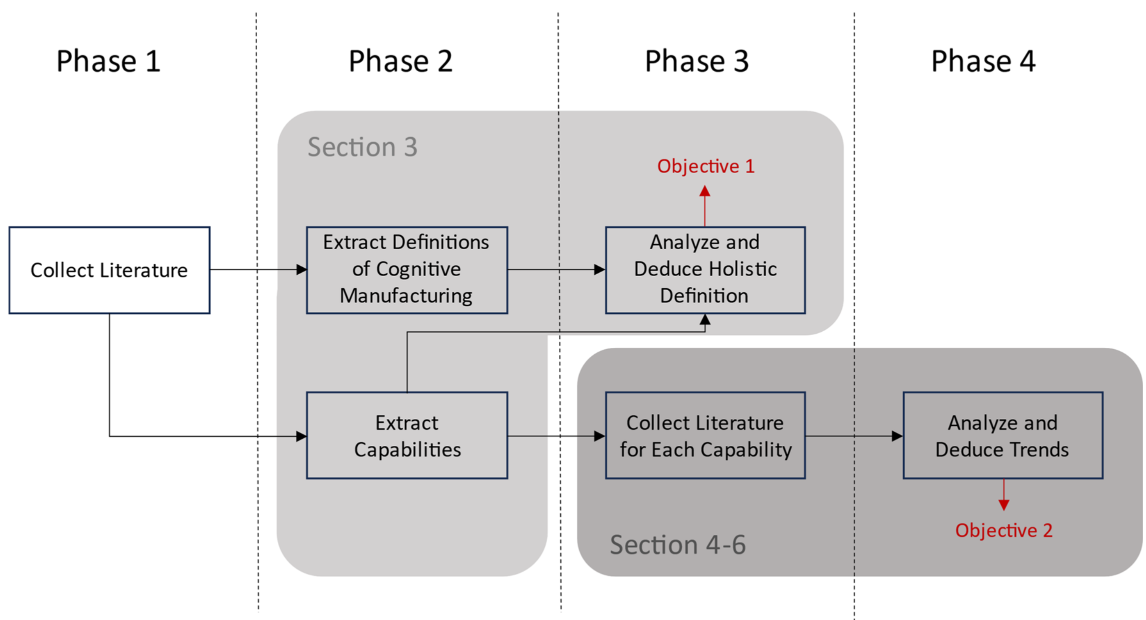

Fig. 2 Systemization of the literature review

then narrowed down to 39 based on the title evaluation of the database. These were further refined to 26 based on the abstract evaluation. However, upon reading these articles, six of them were not accessible by the authors hence the final set contained 20 articles that will be used for the initial investigation. To ensure that content in this review contains only recent works, the search only looked for articles published between 2017 and 2022 which also correlates with the increased interest and publications in this field as shown in Fig. 1. No works prior to 2017 were included so as to ensure that the definition and trends established in this review are relevant and recent enough to be used in this iteration of interest in cognitive manufacturing. The filtering criteria in the title and abstract evaluation were as follows:

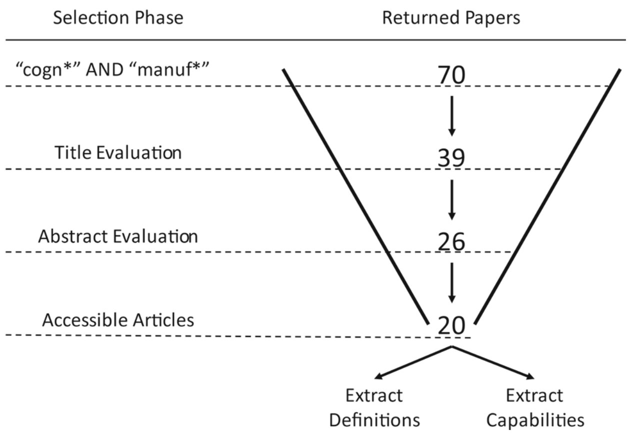

Fig. 3 Article filtering process

- Articles that do not specifically propose or implement a cognitive manufacturing system.
- Articles that focus on one manufacturing process rather than a manufacturing system.
- Articles that do not focus on cognition in the context of manufacturing systems.
- Articles that were not accessible by the author.

Based on that selection process, 20 articles were chosen. Since this represents a small set of papers, instead of a bibliometric analysis, Fig. 4 visualizes the geographic region in which the authors who used the term reside. From this analysis, it is clear that the United States and China are currently the main contributors to this field of research and also showcases that the term has been utilized by different research groups.

These articles were used to achieve the first objective of this review, establishing a definition for cognitive manufacturing. In order to do so, the individual definition of cognitive manufacturing from each paper was extracted. On top of that, these papers were also the bedrock for extracting information about the capabilities of cognitive manufacturing systems which are used for defining the research trends in this field. Even though every article listed contained capabilities for cognitive manufacturing, some did not explicitly state a definition. The section three will delve further into the findings.

Objective 2

Based on the analysis done for objective one, phase three of this review includes another literature collection process in order to define the current research trend within each capability defined in objective one. This collection process was accomplished by iterating through three major journals within the research field: the Journal of Intelligent Manufacturing, the Journal of Manufacturing Systems, and the International Journal of Production Research due to their high impact and direct link with the publication venues for many of the articles in first set collected for this review. Other journals such as Computers in Industry and Computers in Science were also investigated for manufacturing related work. Every volume of these journals published between 2017 and 2022 were investigated and papers were also extracted based on a title and abstract evaluation. The general criteria were that all selected papers must be an implementation article and not a survey or review. On top of that, categorically the selected article must contribute to either the perception, decision making, or reaction capability of the manufacturing system. This was due to the fact that those were the three main capabilities deduced in section four of this review.

This initial selection process at first resulted in 96 publications based on title evaluation, however after filtering out review papers and undergoing abstract evaluation that collection decreased to only 30 publications. After these 30 publications were dissected, further publications were collected through cited papers and further search of specific

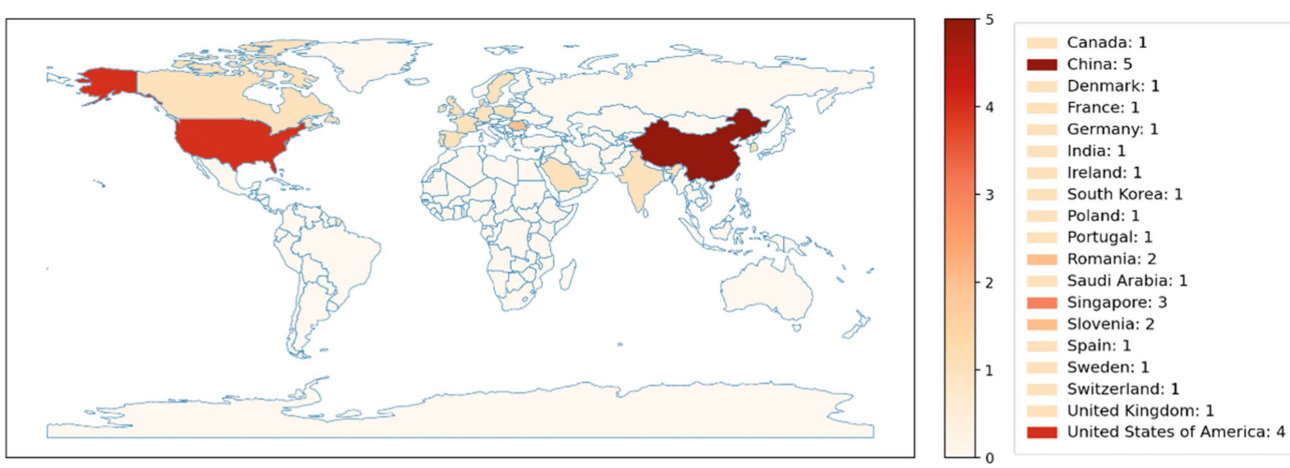

Fig. 4 Author network of the cognitive manufacturing term

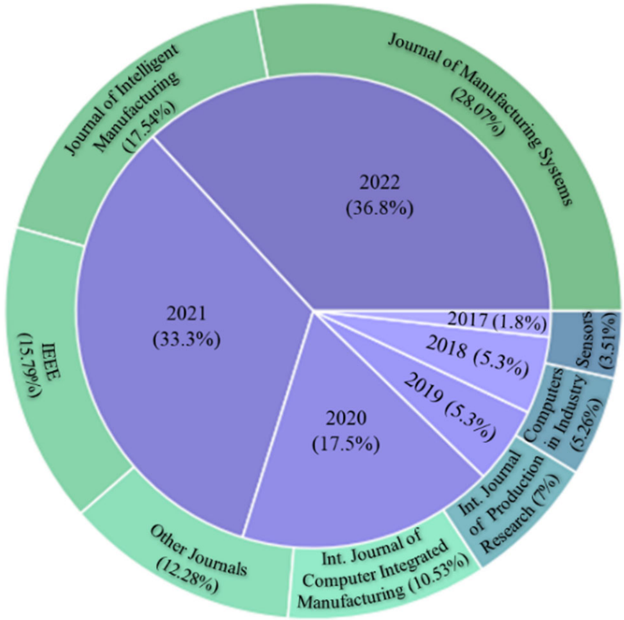

Fig. 5 Publication metrics for capabilities papers

Fig. 6 Word cloud of cognitive manufacturing definitions

technologies to attain 57 papers in total. The bibliographic metrics these papers can be seen in Fig. 5.

Cognitive manufacturing

In this section, a total of 20 references were collected that center on the concept of cognitive manufacturing. These papers are the early works of developing this new era of manufacturing which looks at defining the scope of cognitive manufacturing. The concept of cognitive digital twins has been highlighted throughout these works, however, a definition for cognitive manufacturing can still be refined further. As such, a definition of cognition in the context of manufacturing was extracted from these works in an attempt to frame one formal definition of cognitive manufacturing. The different definitions can be seen in Appendix 1.

As expected, the definitions vary between references depending on the specific focus of each paper. However, some common themes immediately arise at first glance. These themes include awareness, understanding, intelligence, and decision making. All these themes play a vital role in pinpointing an overarching definition.

To be able to create this definition, all the extracted definitions were made into a word cloud, seen in Fig. 6, using TagCrowd (https://tagcrowd.com/) to find the significant terms. To be able to achieve better results, some words were syntactically standardized throughout all the definitions (i.e., Digital Twin changed to DT, real-time vs real time, intelligent to intelligence etc.). This word cloud facilitates the visualization of the most common terms found in these definitions which will be used during the derivation of the definition. Some words will be ignored such as "cognitive", "manufacturing", and "system" as they introduce no added value to the definition.

To analyze the results, recurring words were grouped together to derive an overarching concept which can be included in the definition. These groups were created based on the field of work that they belong to and the role it can satisfy in the definition. For a word to be eligible for categorization, it must have at least two recurrences. The categories were derived as follows:

1) **Category 1: What will Cognitive Manufacturing affect?**
   This category includes words that belong to the manufacturing domain. This category is important to see the specific manufacturing concepts that cognition can play a role in.
2) **Category 2: How will Cognitive Manufacturing have this effect?**
   This category provides the approach or technologies that were mentioned. These words would predominantly pertain to the Computer Science or AI field as they provide technologies that can be used to achieve cognitive manufacturing.
3) **Category 3: Why will Cognitive Manufacturing have an effect?**
   This category is the culmination of the previous two. The words chosen in this category showcase the added capabilities that are introduced with cognitive manufacturing. These words will mostly belong to a hybrid field at the intersection of manufacturing and AI or smart manufacturing.

The populated categories alongside the number of occurrences for each word (in parenthesis) can be seen in Table 1. In category one, words such as "production", and "processes" allude that the concepts of cognitive manufacturing pertain to

Table 1 Categorized key words

Category 1	Category 2	Category 3
tasks (5)	data (6)	planning (3)
system (3)	reasoning (5)	intelligence (5)
production (2)	perception (5)	decision (3)
processes (4)	learning (5)	analytics (3)
maintenance (2)	knowledge (4)	understand (2)
	information (4)	

Table 2 Capabilities of cognitive manufacturing

Reference	Added capability
(Hu et al., 2019)	Intelligent analysis, reasoning, real time monitoring
(Zheng et al., 2021)	Self-configuration and self-optimization
(S. Li et al., 2021)	Human robot collaboration
(Kumar & Jaiswal, 2021)	Decision making
(Krueger et al., 2019)	Planning, autonomous actions
(M. Liu et al., 2022)	Perception, reasoning, and decision making
(Rožanec et al., 2021)	Planning, reasoning, and learning
(Mortlock et al., 2022)	Perception, attention, memory, reasoning problem solving, learning
(Mizanoor Rahman, 2019)	Collaboration
(Dumitrache et al., 2019)	Intelligently use assets, decision making, optimization
(Intizar Ali et al., 2021)	Analyze, understand, and react
(ElMaraghy & ElMaraghy, 2022)	Planning, reasoning, and learning, adaptability
(Gong et al., 2021)	Problem solving, adaptive
(Martín-Gómez et al., 2021)	Perception, reasoning, learning and planning
(Carpanzano & Knüttel, 2022)	React
(Wong & Chui, 2022)	Memory, information processing, feedback
(Seyram et al., 2022)	Reasoning, planning, and solving problems

the full product lifecycle and can help improve each phase of the cycle. Words such as "system" and "tasks" indicate that effects can be felt down to the minor components of manufacturing. As such, within the holistic definition, the full array of manufacturing levels must be encompassed.

The second category will help derive a proper term to use as to how cognition will be attained. From first glance it is clear that "data", "knowledge", and "information" play a key role in achieving such an advanced system. At a more abstract level, that can be incorporated by adopting the term Cyber-Physical, a common term used in the smart manufacturing field of research indicating the intersection between the informational technology with the operational technology.

Finally, the third category can help highlight which key capabilities to include in the definition. To derive an overall theme, words such as "decision", "planning" and "intelligence" can all fit into the idea of intelligence and understanding.

As such, a preliminary definition which can be used to define cognitive manufacturing would be intelligent cyber-physical manufacturing capable of playing a vital role in all aspects of the product lifecycle. However, this definition is still missing a key component which is the specific capabilities that it will be improving.

To accomplish this next step, the 20 articles from the first set were visited again as shown in phase two of Fig. 2, however this time, the specific added capability introduced by that article was extracted in hopes of deducing a greater theme. These capabilities can be seen in Table 2.

From first look, it is evident that cognitive manufacturing introduces a variety of different capabilities to a manufacturing system. Some of these capabilities include autonomous actions (Rožanec et al., 2021), collaboration (S. Li et al., 2021), decision making (Kumar & Jaiswal, 2021), and reasoning (Mladineo et al., 2022). However, to develop the overarching themes for these capabilities, some interdisciplinary study is required. The notion of cognition is a fundamental research topic in psychology. Hence, some ideas from previous studies will be adopted in this review.

Some of the fundamental aspects of cognition include perception, reasoning, and problem-solving (Eysenck & Brysbaert, 2018). Of the cognitive abilities that are available to humans, perception allows the brain to gather information from the world around them to understand the environment and events surrounding them, i.e., perceive the world around them. After this perception, humans can think critically about the information gathered and develop their own knowledge about the world based on their own logic or common sense, allowing them to make decisions for their own actions. Combining these two qualities, humans can react to sudden changes in their surroundings appropriately.

These same qualities can also be seen as pivotal areas of investigation within the AI domain. Cognitive architectures are a section of AI research aiming at creating programs that can reason, develop insights, and adapt to new situations. The objective of these architectures is to model the human mind achieving human-level artificial intelligence (Kotseruba et al., 2018). These architectures specify the underlying infrastructure of intelligent systems and includes

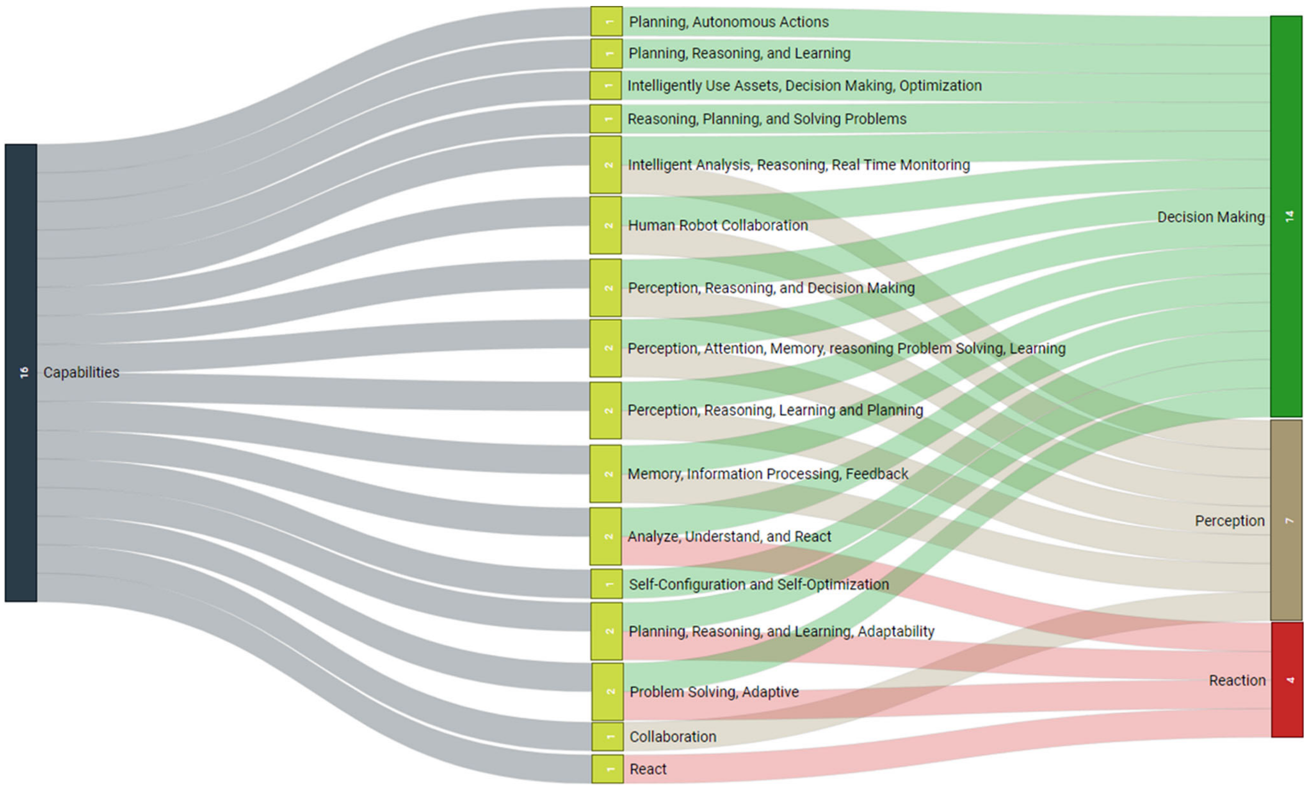

Fig. 7 Categorization of capabilities

consistent aspects across the different application domains such as short and long-term memories, element representation, and the functional processes that operate these structures (Langley et al., 2009). Some of the main capabilities that cognitive architectures focus on include Perception, Attention, Action Selection, Memory, Learning, Reasoning, and Metacognition (Kotseruba et al., 2018).

Based on that, these same capabilities can be adopted in manufacturing systems as cognitive architectures can play a key role in achieving cognitive manufacturing. Even though they can all be integrated into the manufacturing domain, this paper will group the above seven capabilities into three main categories: Perception, Decision making, and Reaction. This is due to the fact that within manufacturing, aspects such as perception, attention, and memory may not have tangible differences when viewing manufacturing systems as a whole. Perception describes the system's ability to understand the events and environment in which it operates, requiring both attention and memory. Decision making highlights the system's ability to apply actionable decisions to the manufacturing process encompassing reasoning and learning, and finally reaction is the system's ability to adapt to unforeseen or new events which ties into reasoning and metacognition. In addition to the psychological rationale for embracing these categories, the identified capabilities also referenced supported these findings as seen in Fig. 7. In this figure, the capabilities extracted were individually detailed within the middle column. The overarching category for each capability was then inferred and is displayed in the third column.

Overall, of the 20 papers used for this analysis, 14 introduced capabilities in decision making such as autonomy, reasoning, self-configuration, and job scheduling. Seven also introduced capabilities in perception such as information exchange, event understanding, and prediction. Finally, four introduced capabilities in reacting such as disruption handling, and adaptability.

Based on this analysis, we can supplement the previous definition of cognitive manufacturing to be intelligent cyber-physical manufacturing capable of perception, decision making, and reacting by utilizing information obtained throughout the whole product life cycle.

To better illustrate this deduced definition, a use case will be used to signify the evolution from autonomous to cognitive manufacturing. We take as an example a manufacturing facility with an automotive assembly line. Figure 8 provides a high level illustration of one specific difference between the autonomous and cognitive manufacturing systems described in this example.

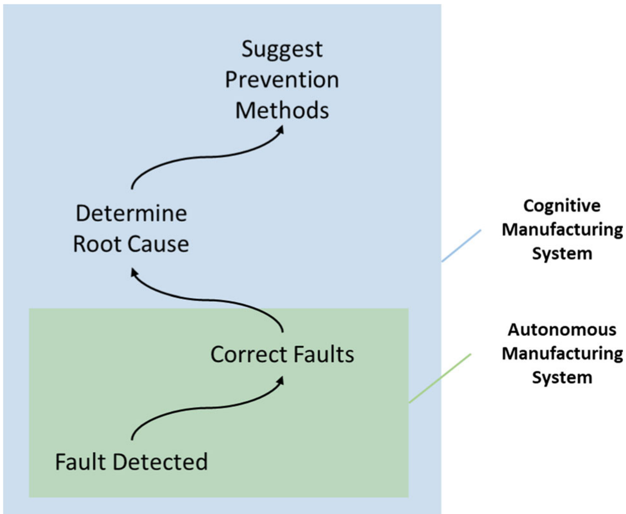

Fig. 8 Illustration of autonomous vs cognitive manufacturing systems

Autonomous manufacturing systems

During the assembly of the car, the different elements of the manufacturing system have autonomy over the upcoming jobs including tasks such as painting and assembly operations. This is due to the dynamic job allocation autonomous systems are capable of accomplishing. When a known failure occurs, the system has the knowledge to overcome this failure and continues production based on the predetermined knowledge infused into the system. Delving further into the painting and assembly operations, specific examples can showcase the capability of each system.

- **Painting:** During the painting process, cracking in the paint film might occur due to extreme humidity. Even though this humidity is monitored, that specific sensor malfunctioned, and the system detects these cracks beginning to form. The system in this case can stop the painting process or reallocate jobs to continue production, however, it will not know the root cause of the problem, hence not mitigating the likelihood of the incident reoccurring and can only recommend an inspection of the station.
- **Assembly:** On an automotive assembly line, different robotic arms can operate synchronously to assemble the different parts of the car chassis. If a part suddenly cracks during the assembly process, the system can detect this crack if trained for it, however, can only halt and reallocate jobs and await human intervention.

Cognitive manufacturing systems

During the assembly of the car, the different elements of the manufacturing system have autonomy over the upcoming jobs to execute. At the same time, this system is employing different technologies to fuse the different data obtained from the assembly line and gain a more holistic perception of the events occurring. The system can decide which subsection of the assembly line needs more attention and interference, alongside creating decisions for dynamic job allocation. The pivotal difference here is the ability for this system to learn on the go by continually taking in the new data to enhance the decision making process and includes reactionary actions which occur when new unencountered events take place on the assembly line. Since this is a new event, the system can utilize all the information that it has to come up with an action which can mitigate erroneous or disastrous consequences.

- **Painting:** Using the same cracking fault from earlier, the cognitive system can use its reasoning capabilities to deduce that the sensor is malfunctioning and react appropriately by using the different information available to it to recommend ordering a new humidity sensor and further rework on the current part.
- **Assembly:** After the crack occurs, the system can react accordingly by finding another part to utilize instead and as a second step utilize the information from the full life cycle (i.e., part supplier, transportation mechanism, manufacturing process) to uncover what caused the part to crack and adapt the manufacturing process of that part to ensure such an issue doesn't occur again.

Perception

This aspect deals with the ability of different manufacturing assets to perceive the status of the production line around them. In that sense, these assets can recognize the different events and operations that are being undertaken at all times. To find the prevalent technologies used in this field of work, articles dealing with the acquisition and processing of data generated in manufacturing shop floors were extracted from the above-mentioned journals. Based on that, there were three recurring topics that were of interest: Semantic Web, Sensor Fusion, and Collaboration.

Semantic web

Information at the time of the inception of the Web was designed for human consumption and did not lend well to the interoperability of that information between machines (Cardoso & Sheth, 2006). As such, Semantic Web attempted to tackle that issue by providing a basis to deal with the massive, dynamic, and heterogenous data (Cardoso & Sheth, 2006).

The main components of the Semantic Web are different entities connected through relationships making up a Knowledge Graph (KG) which is a structured representation of information (Sheth et al., 2019). The main parts of a KG are the nodes (assets, people, objects, or places) and edges (connecting the different nodes together). On top of that, a KG is made up of the Schema/Ontology and the Instantiations. The former defines the classes of the KG and the latter is the specific instant of each class (Parsons, 2009). KGs have been prevalent in applications in Deep Learning (Gaur et al., 2021), Knowledge Representation (Kho et al., 2014), and the medical domain (Xu et al., 2020).

To semantically represent data, Resource Description Framework (RDF) presents an international standard to enhance interoperability between applications. Different entities are depicted in RDF through Uniform Resource Identifies (URI) and is has three main types of entities: subjects, objects, and predicates(Parsons, 2009). Subject and objects can represent the nodes previously defined connected together through predicates.

These technologies enable the next generation of manufacturing systems through their ability to integrate and store data of different modalities. In addition to this, reasoning mechanisms can be introduced to deduce insights and knowledge about the manufacturing system that were previously unattainable. This results in an increased perception of the system as more data is utilized and is accessible for different decision making instances. Works within Semantic Web will be split into four sections: ontology development, KG generation, domain knowledge integration, and reasoning.

Ontologies

Within manufacturing, a prominent field of research is the establishment of various Semantic Web ontologies that could be used to standardize the KG generation process. A standardized ontology would allow different systems to query through KGs and retrieve information in a consistent manner. As such, ontologies in different fields such as the Bosch Industry 4.0 KG was developed which focuses on machines, products, processes, and equipment (Grangel-González et al., 2020). Other ontologies focus more specifically on additive manufacturing (Dinar & Rosen, 2017), and service-oriented business interactions (Lu et al., 2019), and integrating current standards in information modelling such as OPC UA (Schiekofer et al., 2019).

Knowledge graph generation

This topic encompasses research attempting to integrate data sources in a manufacturing facility into a central knowledge graph. In essence this reflects the ability to semantically model the different assets in the facility utilizing the ontologies developed. Real time analog sensor data was integrated into a manufacturing KG using RDF (El Kalach et al., 2023). A novel multi-layer KG was introduced that captures the real-time data obtained from IoT technology in CPPS environments and is continuously updated (M. Liu et al., 2022). Multiple works have in fact constructed an industrial KG which integrates different data sources for further processing (Y.) (B. Zhou et al., 2022) (Grangel-González et al., 2020).

Apart from the integration of live data, different events detected from heterogenous sensors can also be added to the KG for increased perception. Different events detected within IoT streams were integrated into a KG for improved intelligence of the manufacturing system (Karras et al., 2022). On top of that, prediction results from deep learning-based models were attached to the generated KG (B. Zhou et al., 2022). Both these levels of integration can be crucial to realizing a truly cognitive system as it is capable of perceiving data of all different modalities as well as abstract insights and information such as machine and product state.

Domain knowledge

A main benefit of utilizing Semantic Web and KGs is the ability to integrate cross domain information. Cross domain refers to information that is shared about different domains of knowledge, i.e., manufacturing and weather information represent two separate domains. The ability to integrate cross domain information can be crucial to developing the cognitive system's perception as well. The system can utilize information from multiple domains into the manufacturing process. An example could be scheduling power consuming tasks during time spans when utility charges are lower.

One example of this includes the integration of supply chain information with events within the production line (Vlahakis et al., 2018). This can also include product design information (H. Wang et al., 2021), and expert knowledge (Link et al., 2022) (Ladj et al., 2021) and the integration of Manufacturing Execution Systems (MES) (Siafara et al., 2018).

Reasoning

This aspect of perception can prove to be immensely advantageous as it emulates the cognitive abilities of the human brain, which can effectively establish connections between diverse sets of information, leading to a more profound comprehension of various concepts. An example of which could be how the human brain establishes relationships between different types of information in language comprehension. When reading a sentence, the brain processes the meaning of each individual word and then combines them to form a complete understanding of the sentence as a whole. This integration of separate pieces of information allows for a more comprehensive understanding of the message being conveyed. Similarly, the use of a cross domain KGs in IoT technology can facilitate the identification of complex relationships between data sets, enabling better decision making and problem-solving capabilities.

With previous works focusing on creating the KGs, the next advancement is to utilize it for process state information that could be used for decision making processes. This can be done using existing reasoning mechanisms such as Jena (Ameen et al., 2014), Fact++ (Tsarkov & Horrocks, 2006), or Pellet (Sirin et al., n.d.). These reasoners use rules defined by experts to query through the generated KG, identify the satisfied rules based on the information provided in the KG then add or modify the corresponding triple as necessary. This can be seen through work such as (Guo et al., 2021)(El Kalach et al., 2023) and (B. Zhou et al., 2022). These works developed techniques to extract process knowledge, equipment status, and manufacturing process information respectively.

Sensor fusion

Sensor fusion is a field of research dedicated to merging data from multiple sensors so as to achieve a more accurate, comprehensive, and reliable estimate of the environment. There are different aspects of sensor fusion that could be addressed. Different fusion methods being utilized in manufacturing research include Random Forest, Dempster-Schafer theory, feature elimination, Deep Convolutional Neural Networks, Bayesian-based fusion, and information theory (Tsanousa et al., 2022). However, in this paper we will be looking at the two different abstraction levels of sensor data fusion (Vakil et al., 2021)(K. Liu et al., 2018). The Preclassification phase or early fusion which includes both sensor-level and feature-level fusion, and the postclassification phase or late fusion which integrates detected events alongside any decisions or predictions made about the environment. An early fusion approach was adopted with to integrate heterogeneous data based on an intelligent optimization algorithm (Huang, 2020) as well as a late fusion methodology to integrate predictions made from multiple sensor nodes in a quality control and predictive maintenance use case (Wei et al., 2020). Comparisons were also drawn between the different fusion levels to achieve the highest tolerance to missing and noisy modalities (Rahate et al., 2022).

Some advantages of such technologies include improved detectability and reliability of the system (Kong et al., 2020). This capability can be compared to the cognitive ability of the human brain which integrates all different modalities and aspects to obtain an accurate representation of the environment. However, such capabilities still require further research as the computational requirements for technologies such as deep neural networks, signal processing, and feature extraction are great. In addition, while sensor fusion is inspired by the human mind's ability to integrate information from multiple sources, there are still significant differences between the two. The human mind is more complex, adaptable, and robust than current sensor fusion technology.

Collaboration

One key benefit of improved perception is the ability to enhance the collaboration between assets in the manufacturing facility. This is due to the increased understanding of the asset's surroundings. With more information available, different assets can make use of the multimodal data outlined previously to gain an enhanced understanding of the state of different assets around them, which in turn enables more complex collaboration. This vision of cognitive manufacturing is slowly being realized through the incremental works focused on collaboration.

To enhance collaboration, improved perception of all events is required which was tackled through knowledge infusion while utilizing KGs (Wickramarachchi et al., 2022). In that regard, other works also propose enhancing operator performances for better collaboration by providing valuable information about their performance and the state of the production system (Nagy et al., 2022). Vision systems were also investigated as a means for enhancing robot collaborations using semantic segmentation of live feeds (Xia et al., 2021) and intelligent manufacturing systems were developed to increase collaboration within decision making of production in a copper smelting enterprise (Q. Liu et al., 2022).

Digital twins are a big factor in achieving this level of collaboration as they can be used to simulate actions digitally. This is beneficial as simulations can help collaboration be validated quicker and in a safer manner. As such, the fusion of deep learning with digital twins were implemented across multiple works to simulate collaboration between equipment to avoid collision (Xia et al., 2021) and optimize production (P. Wang & Luo, 2021).

Collaboration could also include human robot collaboration to achieve tasks that could not be accomplished through machines alone. As such, this collaboration needs to be seamless with safety a major factor to be considered. Certain works have looked at optimizing this collaboration through task allocation to improve cobot utilization in an assembly line (Gjeldum et al., 2021) and improve communication between the two entities through deep learning to efficiently translate brainwave command phrases to robot commands (S. Liu et al., 2022). On top of that, some works focus on biometric features with deep learning to avoid fatal accidents in smart factories (Abate et al., 2022).

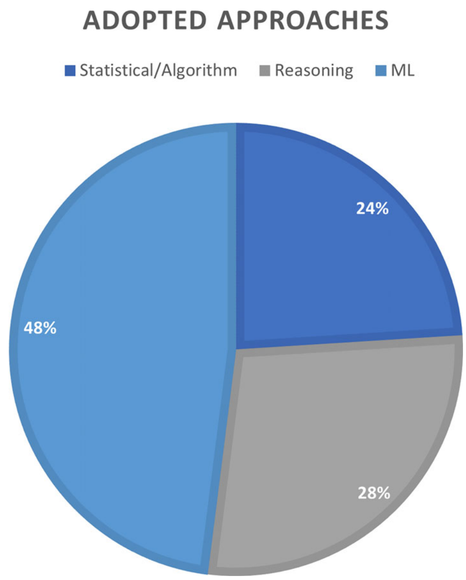

Fig. 9 Decision making in manufacturing

Discussion

Semantic Web, sensor fusion, and collaboration represent the three tangible steps for perception. Semantic Web aids the back end of integrating the multimodal data sources into one central, interoperable, knowledge base. Sensor fusion helps attain a more reliable and holistic estimate of the environment of the manufacturing system. Finally, collaboration showcases an outcome of perception which allows the synchronization of workflows between machines and robots in a timely and safe manner.

Decision making

The capacity to make decisions at the production line is a significant component of cognitive manufacturing systems. Therefore, perception plays a crucial role as the system needs to comprehend real-time events and historical data to arrive at necessary decisions. Cognitive manufacturing systems must be capable of creating holistic decisions based on the heterogenous data generated on the shop floor. These decisions can be adjusted on the go to adapt to new events and job orders.

From the accumulated research works, a few current trends for decision making were analyzed to extract the technologies making waves in manufacturing. 23 papers from the second set of articles were used to determine these current trends. Figure 9 highlights the main approaches used to create decisions in manufacturing systems. 48% of which adopted machine learning techniques, 28% used reasoning mechanisms, and 24% used statistical methods and various algorithms.

Machine learning

Machine learning (ML) provides a great avenue to approach decision making process as it learns the different patterns and relationships within the data. ML focuses on learning systems and algorithms (Qiu et al., 2016) which leverages vast volumes of data to create data driven decisions.

Reinforcement learning

Reinforcement learning is one type of ML which relies on training on agent to act in an environment based of a reward function. The agent traditionally creates decisions which provide the highest rewards defined by the user. Within manufacturing, reinforcement learning was utilized to allow systems to build parts according to user-specified performance indicators (Alam et al., 2020), enhance collaboration between robots working within the same shop floor (Agrawal et al., 2021), and ensure no collisions occur within the manufacturing system (Xia et al., 2021). All these examples showcase the decision making capabilities of reinforcement learning which can play an integral role in cognitive manufacturing.

Supervised learning

Supervised Learning is another subset of ML which uses labelled data to learn patterns within the dataset to be able to produce correct outputs to new data based on the learned inputs. This method can help realize cognitive manufacturing as different works have utilized supervised learning mechanisms to create systems capable of optimizing productivity of a cutting tool in machining lines (Carvalho & Bittencourt, 2021), autonomously perform relocation tasks in a robotic arm (Wheeless & Rahman, 2021), and enhance the load work of inspection stations (Papananias et al., 2020).

Unsupervised learning

Unsupervised learning refers to the training of ML models without the use of annotated data. With this technique the model learns the probability densities of inputs and produces outputs based on the initial data set. This can include technologies such as autoencoders which are used in applications such as anomaly detection. Unsupervised learning can play a key role in cognitive manufacturing by providing a pathway to developing basic decision making capabilities with minimal human intervention. As such, different works have used unsupervised learning to create binary health classification solutions for produced parts (Papananias et al., 2020), dynamic task allocation of unmanned surface vehicles (Ma et al., 2021), and defect inspection (Banf & Steinhagen, 2022).

Statistical methods and algorithms

During this state-of-the-art research, it was found that ML is not the sole approach. Current trends have seen the use of technologies such as statistical methods and reasoners for different systems to create actionable decisions.

Statistical methods are approaches based on mathematical models that attempt to infer future outputs based on probability distributions of data. They aim to make inferences based on a sample of data and use hypothesis testing and confidence intervals to assess the validity of these inferences. Such work can be seen through the generation of an inference matrix for real-time collision detection (Ying et al., 2021), and minimizing total energy consumption and makespan of different products (Chou et al., 2020).

Other implementations focused on scheduling of job orders on the shop floor such as using non-preemptible and preemptible aperiodic task scheduling algorithms for resource planning and task scheduling on edge (Gezer & Wagner, 2021), spatial temporal analytics for real-time advanced planning and scheduling (M. Li et al., 2022), and scheduling algorithms alongside deep neural networks (Iqbal et al., 2022). Some implementations also focused on personalized production by utilizing the HUMANT algorithm to determine the optimal configuration based on user preferences (Mladineo et al., 2022).

Reasoning

Recent research has also shown a prevalence of reasoning mechanisms that aim to derive knowledge and make decisions. Reasoning mechanisms are logic or rule-based approaches that attempt to utilize information to infer or deduce implicit knowledge and make actionable decisions. This approach is closely coupled with Semantic Web as reasoning mechanisms are deployed on KGs to create new entities and triples to further describe the state of different entities. This technology can be used to automate process decision making (Guo et al., 2021), demand forecasting and production planning (Rožanec et al., 2021), and adapt to changes in job orders and operation failures (Wan et al., 2022).

Discusion

Innovation within decision making has been rapid, especially with the recent breakthroughs in AI technologies. This advancement can be seen in certain cornerstones of manufacturing systems, however in the cognitive manufacturing paradigm these advancements can be seen through the utilization of the increased perception of manufacturing systems. As seen in the previous section, new technologies have been adopted within manufacturing to integrate heterogenous data to be used in manufacturing systems. In order to see the utilization of this data, the same pool of 23 papers were investigated again to uncover how frequently this heterogenous data is used in the decision making process. Table 3 summarizes the findings of this experiment.

The three categories of data used for this experiment are as follows. Sensor data refers to data being generated by sensors within the manufacturing shop floor. High level information encompasses information formulated higher up the vertical chain of the manufacturing facility. This can include information present in MES and ERP systems such as scheduled jobs, available resources, and abstracted information about the current state of the shop floor. Finally, domain knowledge refers to information that is injected into the system from different domains whether that is publicly available information from the web or knowledge traditionally gained from years of experience in the field by domain experts.

The results showcase an emerging trend in the utilization of different modalities of data. Of the 23 articles, sensor data was used eight times, higher level information in 16, and domain knowledge in four. An initial observation of these figures might indicate that utilizing higher-level information is the most advanced among the three categories. However, a more comprehensive analysis could reveal a different perspective. Utilizing sensor data is a well-established field with years of development in fields such as time-series analytics (Farahani et al., 2023) and predictive maintenance (Saidy et al., 2020). With those fields already saturated, researchers have switched their focus to adopting these new data sources for enhanced decision making. As such, Table 3 clearly shows the emerging trend of using this higher-level information.

One clear gap within the sample pool chosen for this review is the lack of papers that utilize all three types of information. This presents a clear disconnect between the two discussed capabilities. Despite the significant progress observed in the perception paradigm for integrating various data sources, there hasn't been the corresponding development or progression stemming from it.

Reaction

The third capability of cognitive manufacturing systems can be thought of as the culmination of all the previous two capabilities. With the system capable of acquiring heterogenous data from the shop floor, and utilizing decision making techniques, the cognitive system will be able to combine those two mechanisms to create decisions on the fly with ever

Table 3 Inputs for decision making

Reference	Sensor data	High level information (jobs, resources, environment)	Domain knowledge
(Rossit & Tohmé, 2022)			✔
(Oluyisola et al., 2022)		✔	
(Nannapaneni et al., 2021)		✔	
(Ma et al., 2021)	✔		
(Mladineo et al., 2022)			✔
(Cao et al., 2021)		✔	
(Zheng et al., 2021)		✔	
(Guo et al., 2021)		✔	
(Rožanec et al., 2021)	✔		
(B. Zhou et al., 2022)	✔		
(W. Chen et al., 2020)	✔	✔	
(Gezer & Wagner, 2021)		✔	
(Ying et al., 2021)		✔	
(Wan et al., 2022)	✔	✔	
(G. Zhou et al., 2019)	✔	✔	
(Ye et al., 2020)		✔	✔
(G. Chen et al., 2021)	✔		
(Kuhnle et al., 2021)		✔	
(X. Wang et al., 2022)		✔	
(Xia et al., 2021)		✔	
(Iqbal et al., 2022)	✔		
(M. Li et al., 2022)		✔	
(Chou et al., 2020)		✔	✔

changing circumstances. This can be thought of as the ability to react accordingly.

In the context of manufacturing, this can be related to disruption handling (Darmoul et al., 2013). Disruption handling refers to the ability for a production system to react to unforeseen disturbances. These disturbances can range from internal errors (Machine failure, product breaking) or external stimuli (introduction of foreign factors into the manufacturing environment).

Previous works

Within the literature gathered for this review very few works had been able to showcase a truly reactive system as described. A total of six papers had been deemed to suit this specific capability. For a paper to be included, the work must showcase the capability for a system to react to specific disturbances whether reactively or proactively. Due to the scarcity of relevant articles, established methodologies could not have been extracted for this capability. However, with the maturity of this field, trends shall emerge with time.

From the extracted articles however, some works have attempted to achieve a response to abnormal events occurring during product assembly by attempting to predict them before they take place (Y. Wang et al., 2021). This was done through the Grey-Markov method, an ensemble of the Grey model and Markov Chains, for an effective prediction system capable of predicting equipment failures accurately. Another prediction framework was proposed based on situation awareness which perceives the current state of the production system(Eirinakis et al., 2021).

Beyond prediction, the system response was also investigated. The recovery plan for a disrupted single-stage multi-product production system was also studied to minimize cost deficit of disruptions. Recovery planning was done through pattern search and genetic algorithms (A. I. Malik & Sarkar, 2020). Different works focused on disturbance identification based on a Cyber-Physical Production System. Based on the identified disturbance, adaptive scheduling was applied to a semiconductor manufacturing system (Qiao et al., 2020). To adapt to current conditions, a Reinforcement learning mechanism was developed which updates flow of material based on real time sensor data and other monitoring devices (Kumar et al., 2020). Another control mechanism that was implemented involves an Analytic Hierarchy Process with expert rules applied to a dispatching problem in an assembly process to adapt to disturbances in production (Attajer et al., 2022). Specific external disruptions could include shifts in the market, prompting the development of a machine learning context-aware manufacturing system to effectively respond to varying demands (Ye et al., 2022).

Discussion

Within these papers three categories were of specific interest, the events the system had to react to, the method used to achieve it, and the requirement of human intervention for proper reaction. Events and human were investigated as they present an important metric to the level of intelligence that the manufacturing systems have reached, whereas the methods

Table 4 Summary of reaction capability trends

Paper	Event types	Method
(Y. Wang et al., 2021)	Abnormal assembly	Grey-markov method
(Eirinakis et al., 2021)	Events such as delivery delays, urgent orders, and machine breakdown	Event detection and predictive analytics
(A. I. Malik & Sarkar, 2020)	Resource shortages, power issues, and halt in production	Pattern search and genetic algorithm
(Qiao et al., 2020)	Machine breakdowns and rush orders	GA and KNN
(Kumar et al., 2020)	Reacts to income of new information about environment	Reinforcement learning and Kalman filter
(Attajer et al., 2022)	Various	Analytic hierarchy process, product-driven control, and machine learning

were discovered in order to extract the technologies that can be used for this capability. Table 4 provides a summary of the findings.

These observations indicate a distinct transition toward the use of machine learning techniques to accomplish a reaction mechanism. Nonetheless, in some cases, these methods may need additional enhancement, whether through the integration of an Analytic Hierarchy Process (a Multi-Criteria Decision Making technique) or the application of Kalman Filters.

Overview of trends and industrial solutions

Overview of trends

After careful investigation, Table 5 provides a summary of all the mentioned works within the previous three sections. The motivation behind this table is to provide an intuitive look at the current state of the art of the capabilities being developed for cognitive manufacturing.

Upon examination of this overview, some overlaps can be identified between the technologies within each capability. As an example, reasoning can be used to both increase the perception of the manufacturing system and as a means to create decisions, Reinforcement learning was used for regular decision making and to aid in reaction, and different ML techniques were augmented with filters or algorithms for increased reaction capacity. Even with this overlap, to the author's knowledge, none of the developed systems can be categorized as truly cognitive. Apart from the shortcomings discussed within each capability, none has integrated all three capabilities together. At present, this research field lacks a fully developed system capable of effectively integrating the diverse modalities of data discussed in this review and utilizing this data systematically for decision making and reaction.

Table 5 Overview of cognitive manufacturing trends

Capability	Trends	Technology
Perception	Semantic web	Resource description framework
		Knowledge graphs
	Sensor fusion	Bayesian based fusion
		Deep CNNs
		Dempster-schafer theory
		Random forest
	Collaboration	Deep learning
		Semantic segmentation
		Digital twin simulation
		Knowledge infused learning
Decision making	Machine learning	Reinforcement learning
		Supervised learning
		Unsupervised learning
	Statistical methods	Scheduling algorithms
		Spatial temporal analytics
		Inference matrix
	Reasoning	Rule based reasoning mechanisms
Reaction	N/A	Analytical hierarchy process
		Reinforcement learning
		Disturbance identification and adaptive scheduling
		Pattern search and genetic algorithms
		Grey-markov model

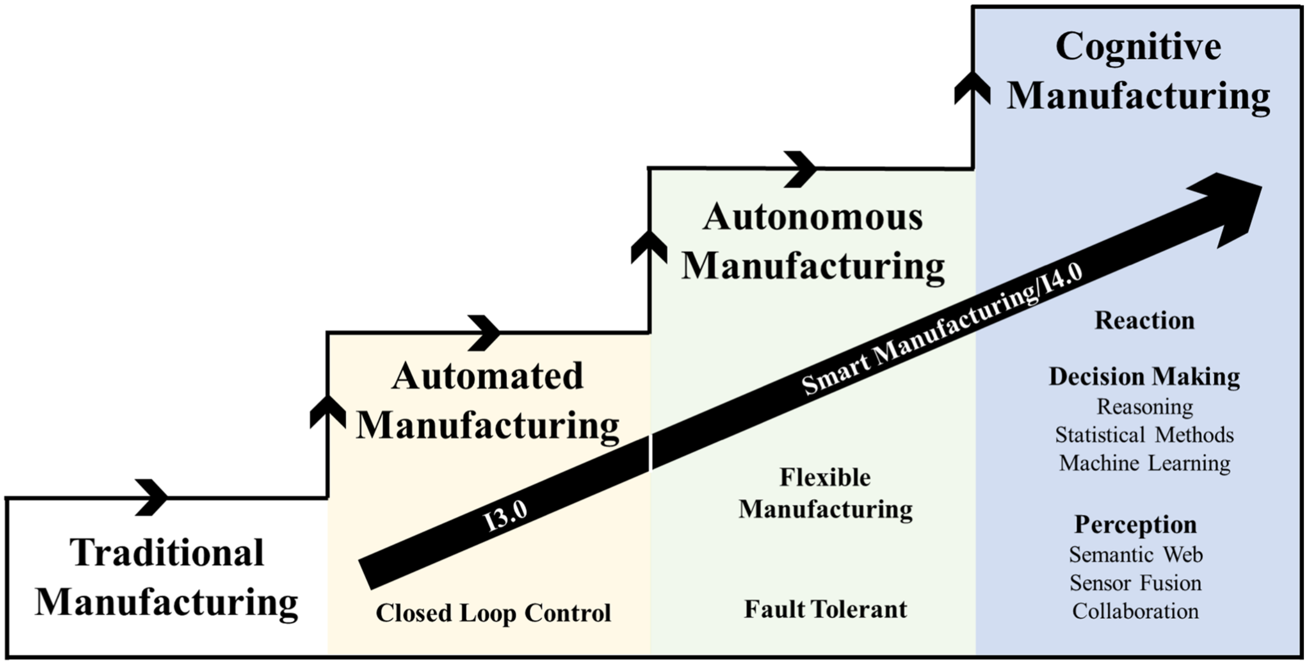

Fig. 10 Evolution of manufacturing systems

Industry solutions

With the advantages brought forth by cognitive manufacturing, it is of little surprise that manufacturing companies have begun to adopt it as a future solution to the current issues faced within facilities. In fact, some companies have already worked on solutions to service manufacturers' needs within the realm of Cognitive Manufacturing. Enterra Solutions created the Enterra Enterprise Cognitive System (AILA) (*Industry 4.0: The Emergence of Cognitive Manufacturing—Enterra Solutions*, n.d.) which is a system designed to enhance decision making capabilities in the smart manufacturing era. Some key features include managing asset performance, enhancing process and quality, and optimization of supply chain and resource. This is done by utilizing data from heterogenous sources such as equipment, sensors, logs, manuals, and employee biometric monitors. Bristlecone has also embraced cognitive manufacturing (*Cognitive Manufacturing & Industry 4.0 Supply Chain Solutions | Bristlecone*, n.d.) to enhance design-to-production processes for increased speed and intelligence. This approach accelerates time to market, prolongs asset lifespan, and leverages manufacturing insights, interconnected assets, intelligent automation, and digital quality.

Infosys has also focused on integrating various data sources and key performance indicators (KPIs) to establish a control loop for sensing, learning, reasoning, and responding (*Enterprise Cognitive Platform for Infused Intelligence | Infosys*, n.d.). Infosys' cognitive technology platforms incorporate features such as image recognition and natural language processing. These AI-driven solutions facilitate self-diagnosis, leading to reduced process lead times and enhancements in planning and real-time operations. These solutions proactively address issues on the shop floor and within the supply chain to mitigate disruptions. Finally, IBM have provided a comprehensive roadmap for the evolution of current manufacturing system to cognitive systems (Bonnaud et al., n.d.). This includes a four step process which utilizes IBM solutions to gather data, visualize patterns, advance analytics, and digitalization, and infuse systems with cognitive capabilities. These capabilities encompass innovative methods for handling unstructured data, which includes imagery, video, and audio, alongside the application of machine-learning algorithms.

Therefore, it is clear that there is a growing interest in advancing cognitive manufacturing within industry. The current status of these solutions aligns with the research conducted in the perception capabilities discussed in this review, as many of these solutions effectively integrate various data sources. Additionally, some of these solutions introduce decision making capabilities, such as task scheduling and dynamic supply chain management. However, it is important to note that the reaction capability of manufacturing systems remains an essential aspect of cognitive manufacturing systems that has yet to be fully addressed. This highlights a critical area for further development in future research, and it is possible that more solutions focused on reactive capabilities will emerge in the coming years.

Conclusion

The manufacturing field has witnessed relentless evolution to enhance the capabilities of manufacturing systems as seen in Fig. 10. Automated Manufacturing systems were introduced capable of closed loop control for mass production. This later evolved into the current strides in autonomous manufacturing capable of creating flexible and fault tolerant manufacturing systems (Patel et al., 2018). However, the future of manufacturing systems requires cognitive systems capable of perception, decision making, and reaction as outlined in this review.

This paper sought to achieve two objectives throughout the review process. The first was to establish a definition for cognitive manufacturing and the second was to highlight the current research trends within the cognitive manufacturing field. This was done by gathering peer reviewed publications in major journals within the smart manufacturing field between 2019 and 2022. Based on the methodology outlined in section two, the final adopted definition was: intelligent cyber-physical manufacturing capable of perception, decision making, and reacting by utilizing information throughout the whole product life cycle.

The capabilities mentioned in the definition were further expanded to study the trends and technologies currently present in the Cognitive Manufacturing research field. Shortcomings for each trend were investigated alongside an overview of all the findings which can be found in Table 5. This led to the discovery of some overlap between capabilities and gaps in implementations.

Overall, this review serves the purpose of being the bed rock for future research in the cognitive manufacturing field for the coming years by highlighting the current directions and state of the art. Moving forward, more effort must be made in creating a manufacturing system and utilizing manufacturing datasets such as (Harik et al., 2024), which can satisfy every part of the adopted definition.

Appendix 1

Appendix 1 Cognitive manufacturing definitions

Reference	Cognitive definition
(Hu et al., 2019)	*"Realize the efficient data collection, automatic production, intelligent recognition and analysis, and active operation and maintenance of the iRobot-Factory."*
(Zheng et al., 2021)	Self-configuration, Self-optimization, Self-adaptive
(Chung et al., 2019)	*"Analyze a variety of data associated with a traceability system, post-by-post scalability infrastructure, and workers' work system through the information exchange of the data collected in real time, and to establish an improved system through data mining."*
(Kumar & Jaiswal, 2021)	*"Enables organizations to actively use the advanced analytics to understand, reason, and learn the processes, people, and operations"*
(M. Liu et al., 2022)	*"Cognitive manufacturing applies cognitive intelligence in the manufacturing field, empowers industrial manufacturing systems with cognitive capabilities, perceives changes in the production process, and performs a series of reasoning and decision-making tasks."*
(Rožanec et al., 2021)	*"Cognitive technologies perform AI-based supplementary tasks that help make better decisions and complete objectives and tasks that usually require human intelligence, such as planning, reasoning, and learning."*

Reference	Cognitive definition
(Mortlock et al., 2022)	*"Fundamental aspects of cognition include attention (selective focus), perception (forming useful precepts from raw sensory data), memory (encoding and retrieval of knowledge), reasoning (drawing inferences from observations, beliefs, and models), learning (from experiences, observations, and teachers), problem-solving (achieving goals), knowledge representation,* etc.*"*
(Dumitrache et al., 2019)	*"a combination of IoT and analytics (or AI) meant to make full use of the enterprise data and information, from the design to shop floor maintenance"*
(Intizar Ali et al., 2021)	*"Cognitive digital twins will convert traditional digital twins into smart and intelligent agents that can access, analyze, understand, and react to their current status."*
(ElMaraghy & ElMaraghy, 2022)	*"Cognitive technologies perform AI-based supplementary tasks that help make better decisions and complete objectives and tasks that usually require human intelligence, such as planning, reasoning, and learning."*
(Martín-Gómez et al., 2021)	*"They differ from other technical systems in that they perform cognitive control and have cognitive abilities such as perception, reasoning, learning and planning, with a specific architecture."*
(Carpanzano & Knüttel, 2022)	*"These cognitive processes consist of the perception of the environment, its interpretation, the crosslink with existing knowledge and the subsequent decision with a coupled action"*
(Sira, 2022)	*"Extracts applicable information together automatically and employs analytics to get an understanding of the manufacturing process. It robotizes reactions towards its findings and offers practical information being able to steadily deliver updated knowledge to decision-makers"*
(Seyram et al., 2022)	*"Using machines to utilize technologies that mimic human cognitive abilities to solve complex problems in manufacturing."*

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Declarations

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Disclosure of A.I usage to complete this work During the preparation of this work, the author(s) used "ChatGPT" to improve the readability, grammar correction, and language of the paper. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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