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Artificial intelligence-based decision-making algorithms, Internet of Things sensing networks, and sustainable cyber-physical management systems in big data-driven cognitive manufacturing

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Keywords: *cognitive manufacturing; Artificial Intelligence of Things; cyber-physical system; big data-driven deep learning; real-time scheduling algorithm; smart device; sustainable product lifecycle management*

Abstract

Research background: With increasing evidence of cognitive technologies progressively integrating themselves at all levels of the manufacturing enterprises, there is an instrumental need for comprehending how cognitive manufacturing systems can provide increased value and precision in complex operational processes.
Purpose of the article: In this research, prior findings were cumulated proving that cognitive manufacturing integrates artificial intelligence-based decision-making algorithms, real-time big data analytics, sustainable industrial value creation, and digitized mass production.
Methods: Throughout April and June 2022, by employing Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) guidelines, a quantitative literature review of ProQuest, Scopus, and the Web of Science databases was performed, with search terms including "cognitive Industrial Internet of Things", "cognitive automation", "cognitive manufacturing systems", "cognitively-enhanced machine", "cognitive technology-driven automation", "cognitive computing technologies," and "cognitive technologies." The Systematic Review Data Repository (SRDR) was leveraged, a software program for the collecting, processing, and analysis of data for our research. The quality of the selected scholarly sources was evaluated by harnessing the Mixed Method Appraisal Tool (MMAT). AMSTAR (Assessing the Methodological Quality of Systematic Reviews) deployed artificial intelligence and intelligent workflows, and Dedoose was used for mixed methods research. VOSviewer layout algorithms and Dimensions bibliometric mapping served as data visualization tools.
Findings & value added: Cognitive manufacturing systems is developed on sustainable product lifecycle management, Internet of Things-based real-time production logistics, and deep learning-assisted smart process planning, optimizing value creation capabilities and artificial intelligence-based decision-making algorithms. Subsequent interest should be oriented to how predictive maintenance can assist in cognitive manufacturing by use of artificial intelligence-based decision-making algorithms, real-time big data analytics, sustainable industrial value creation, and digitized mass production.

Introduction

Edge computing technologies, convolutional neural networks, and situational awareness algorithms configure event modeling and forecasting in big data-driven cognitive manufacturing. Data mining tools, predictive analytics algorithms, and sensor–actuator networks articulate autonomous control systems. Visual perception tools, deep learning algorithms, and object recognition processes assist robotic navigation systems. Context recognition tools, data fusion technologies, and collaborative operation mechanisms enable reconfigurable manufacturing processes. Sensing and actuation capabilities, decision and control algorithms, and edge and fog computing technologies further remote intelligent object and image detection, identification, and recognition. Vision and navigation systems, cloud computing machines, and contextual data monitoring tools shape intelligent simulation environments. Artificial neural networks, context awareness tools, and visual cognitive algorithms optimize robotic manufacturing processes.

The purpose of this systematic review is to analyze recently published literature on how artificial Intelligence of Things-based cognitive manufacturing networks (Cug *et al*., 2022; Kovacova *et al*., 2022a, 2022b; Lyons, 2022a; Robinson, 2022) having an increased level of automation (Dawson, 2022; Kliestik *et al*., 2022a; Poliak *et al*., 2022; Rice, 2022) integrate massive machine-sensed multimodal data (Sharma *et al*., 2021; Woo *et al*., 2020), neural network-based embedding and cognitive manufacturing control algorithms (Altaf *et al*., 2021; Chang *et al*., 2021; Chung *et al*., 2019; Perzylo *et al*., 2019), and enhanced operational adjustability and efficiency (Maier *et al*., 2010; Zeba *et al*., 2021; Zheng *et al*., 2021) in the direction of mass personalization and smart adaptive systems. We want to elucidate whether the integration of artificial intelligence data-driven Internet of Things systems and real-time advanced analytics (Kumar & Jaiswal, 2021; Li *et al*., 2021a; Zhao & Xu, 2010; Krüger *et al*., 2016) has furthered the swift advancement of Internet of Things-based real-time production logistics.

In this research, prior findings have been cumulated (Li *et al*., 2015; Palombarini & Martínez, 2012; Siafara *et al*., 2018; Din *et al*., 2019) clarifying that artificial intelligence data-driven Internet of Things systems (Cavallo *et al*., 2021; Chung & Yoo, 2020; Li *et al*., 2021b; Qin & Lu, 2021), deep learning-assisted smart process planning (Elia & Margherita, 2021; Gain, 2021; Liu *et al*., 2022; Penumuru *et al*., 2020), and real-time sensor networks (Ferreras-Higuero *et al*., 2020; Ksentini *et al*., 2021; Hu *et al*., 2016; Ding *et al*., 2021) advance constantly optimized smart manufacturing systems. In this research, previous published findings have been cumulated clarifying that cognitive capabilities lead to increased flexibility and variability (Dumitrache *et al*., 2019; Emmer *et al*., 2018; Casadei *et al*., 2019; Hu *et al*., 2019) that enable streamlined production. The research problem and the literature gap developed thoroughly in the systematic review is whether the integration of artificial intelligence data-driven Internet of Things systems and sensing networks, autonomous decision-making algorithms, sustainable product lifecycle management, and real-time advanced analytics has furthered the swift advancement of cyber-physical production logistics in relation to cognitive manufacturing.

This is the first systematic review covering cognitive capabilities (Lăzăroiu *et al*., 2017; Nagy & Lăzăroiu, 2022; Valaskova *et al*., 2022) of the smart manufacturing systems, as an extension of a hot emerging topic hardly covered in the literature (Andronie *et al*., 2021a, 2021b, 2021c; Lăzăroiu *et al*., 2022). We supplement prior research by consistently proving that computer vision algorithms harness image recognition tools, context aware systems, and machine learning techniques. Cyber-physical production systems deploy predictive modeling algorithms, image processing tools, and blockchain technologies in Industry 4.0-based networked environments. Smart manufacturing machines leverage robotic coordination mechanisms, decentralized data analytics, and visual tracking algorithms across intelligent connectivity infrastructures. Robotic manufacturing processes develop on cognitive decision-making algorithms, ambient intelligence tools, and distributed sensor networks. Robotic navigation systems and industrial wireless sensor networks integrate intelligent data processing tools, multiple smart agents, and object perception algorithms. Multi-machine cooperation tools require situational awareness algorithms, ambient intelligence tools, and image recognition processes in synthetic simulation environments.

The manuscript is organized as following: methodology (Section 2), artificial Intelligence of Things-based cognitive manufacturing networks (Section 3), cutting-edge cognitive computing, big data analytics techniques, and Industrial Internet of Things in smart manufacturing systems (Section 4), cyber-physical systems, big data-driven deep learning, and real-time scheduling algorithms in cognitive manufacturing (Section 5), discussion (Section 6), conclusions (Section 7), specific contributions to the literature (section 8), limitations and further directions of research (Section 9), and practical implications (10).

Methods

Throughout April and June 2022, a quantitative literature review of ProQuest, Scopus, and the Web of Science databases was performed, with search terms including “cognitive Industrial Internet of Things”, “cognitive automation”, “cognitive manufacturing systems”, “cognitively-enhanced machine”, “cognitive technology-driven automation”, “cognitive computing technologies,” and “cognitive technologies.”, i.e., the most employed words or phrases across the analyzed literature. As the inspected research was published between 2010 and 2022, only 344 articles satisfied the eligibility criteria.

By eliminating questionable or imprecise findings (limited/nonessential data), outcomes unsubstantiated by replication, too general material, or having somewhat similar titles, 51, chiefly empirical, sources were selected (Tables 1 and 2). For the PRISMA flow diagram, a Shiny app was deployed as regards evidence-based gathered and processed data, SRDR Web-based collaborative resource was pivotal in configuring refined extraction forms, articulating the study design, MMAT assessed content validity and suitability of screening questions, determining quality criteria and score, AMSTAR (Assessing the Methodological Quality of Systematic Reviews) leveraged artificial intelligence and intelligent workflows, and Dedoose was used for mixed methods research. VOSviewer layout algorithms and Dimensions bibliometric mapping were deployed as data visualization tools, and the search outcomes and screening were displayed by a PRISMA flow diagram (Figure 1).

Citation correlations as regards co-authorship have covered how machine learning algorithms, plant maintenance scheduling and sensor data fusion tools, and industrial automation devices are pivotal in smart connected objects. Cloud computing technologies, context awareness algorithms, and ambient intelligence tools are instrumental in autonomous robotic systems. Image recognition algorithms, smart environment modeling tools, and real-time event analytics configure mobile autonomous robots. Data visualization functionalities, wireless sensor networks, and computer vision algorithms articulate computation task cooperation and production process modeling in smart factories. Spatial data acquisition tools, remote sensing algorithms, and computer vision control techniques assist behavior pattern clustering of mobile robotic devices and autonomous multi-robot systems (Figure 2).

Citation correlations as regards citation have covered how environment perception sensors, data processing algorithms, and signal processing tools enable virtual machine interoperability across autonomous manufacturing systems. Smart interconnected devices, sensor fusion capabilities, and deep reinforcement learning tools further cognitive and cloud robotics. Swarm robotic algorithms, image recognition technologies, and natural language processing tools shape autonomous task allocation and contextual data monitoring. Distributed intelligence tools, fault diagnosis algorithms, and immersive visualization technologies optimize mobile robotic devices in smart interactive environments. Mobile robot technologies harness autonomous cognitive systems, data stream clustering algorithms, and computational intelligence tools (Figure 3).

Citation correlations as regards bibliographic coupling have covered how robotic operating systems deploy image processing tools, object recognition algorithms, and machine intelligence technologies across collaborative industrial environments. Robotic autonomous systems leverage image recognition algorithms, data acquisition tools, and multi-sensor fusion technologies. Multi-agent robotic systems and autonomous swarm robots develop on path planning algorithms, cognitive artificial intelligence tools, and data fusion mechanisms in smart manufacturing environments. Robotic and sensor devices integrate image recognition algorithms, data analytics technologies, and vision and navigation systems in distributed computing networks. Computation-enabled robotic devices and virtual machines require object recognition algorithms, visual perception tools, and industrial automation technologies across distributed interoperable environments (Figure 4).

Citation correlations as regards co-citation have covered how multisensor fusion technologies, deep convolutional neural networks, and image processing tools are pivotal in collaborative autonomous systems throughout robotic swarm operations. Environment perception sensors, situational awareness algorithms, and spatial data processing tools are instrumental in multiple autonomous mobile and cloud networked robots. Big data management tools, context awareness algorithms, and visual and spatial intelligence technologies configure robotic device capabilities in dynamic manufacturing environments. Captured image data and cognitive artificial intelligence tools, remote sensing and crowd navigation algorithms, and collaborative localization techniques articulate object perception operations in mobile autonomous robots. Sensing and computing technologies, autonomous visual object detection tools, and spatial cognition algorithms assist robotic operating systems (Figure 5).

Artificial Intelligence of Things-based cognitive manufacturing networks

The processing of materials tends to be increasingly automated with the growing implementation of robotics and industrial automation in cyber-physical system-based smart factories. The processing of data has been computerized by the integration of software programs (Cug *et al*., 2022; Michalkova *et al*., 2022; Sharma *et al*., 2021) for material demand and inventory planning, industrial big data analytics, Internet of Things-based real-time production logistics, and robotic process automation. Internet of Things sensing networks assist scanning technologies in generating the required data for machine learning-enabled processes. Automation of both production and business operations is carried out by harnessing software programs that employ fixed procedural logic to scramble human judgment by using cognitive decision-making algorithms. Developments in sensor technologies are optimizing both the scope and scale of information (Kumar & Jaiswal, 2021; Robinson, 2022; Sharma *et al*., 2021) that can be acquired in digital form. Storing big data quantities is essential for adequately training machine learning algorithms. With the transition towards smart manufacturing, huge quantities of data are being produced by artificial intelligence data-driven Internet of Things systems. Machine vision systems configure sensing technologies, constituting an important asset for any production phase that necessitates accurate, swift, and constant repetitive assessment of manufactured item specification and quality. Imaging installation can be instrumental in attaining amplified precision and promptness in visual analysis of products, leading to the cancelation of expensive manual scrutiny and heightened product quality. The performance and lowness in price of vision sensors have escalated significantly due to developments in camera devices and image processing algorithms.

In a cognitive industrial unit, product manufacturing is robotically planned and itemized (Altaf *et al*., 2021; Chang *et al*., 2021; Maier *et al*., 2010; Zeba *et al*., 2021; Zheng *et al*., 2021), harnessing a knowledge base configuring component capabilities and processes of the shop floor. A factory knowledge base, by use of component capabilities and behavior, configures the intelligent capabilities of industrial units in cyber-physical system-based smart factories. In cognitive manufacturing, an assembly line sets up the production process courses of action for distinct products through deep learning-assisted smart process planning and artificial intelligence data-driven Internet of Things systems. Cyber-physical systems, big data-driven deep learning, and real-time scheduling algorithms (Chang *et al*., 2021; Michalkova *et al*., 2022; Perzylo *et al*., 2019) articulate cognitive manufacturing. The integration of artificial intelligence data-driven Internet of Things systems and real-time advanced analytics has furthered the swift advancement of Internet of Things-based real-time production logistics that inspect and react to external stimuli by use of cognitive decision-making algorithms for business process optimization. Internet of Things has developed a thoroughly networked world driven by heterogeneous wireless sensors producing massive volumes of data in various fields and applications. Deep learning-assisted smart process planning can enable predictive analytics and big data-driven decision-making operations. Smart manufacturing systems are progressively equipped with perceptive capabilities (Lyons, 2022a; Robinson, 2022; Sharma *et al*., 2021) by use of cutting-edge cognitive computing, big data analytics techniques, and Industrial Internet of Things. The latter has designed the industrial sector by creating groundbreaking applications whose objects and nodes network to gather, exchange, and inspect a massive volume of sensing data by employing techno-social systems. Massive volumes of Internet of Things information can be acquired as big data useful in deploying deep neural network learning algorithms for product decision-making information systems, Internet of Things-based real-time production logistics, and sustainable organizational performance in smart networked factories.

The cutting-edge enhancements in production operations (Sharma *et al*., 2021) arise out of developments in cognitive capabilities. With cognitive technologies progressively integrating themselves at all levels of the manufacturing enterprises, robots and automated technologies make decisions by use of industrial big data analytics in Internet of Things-based real-time production logistics, deep learning-assisted smart process planning, and cyber-physical process monitoring systems in networked factories. Machines are getting considerably harmonized with sensors and interpretation algorithms (Cug *et al*., 2022; Maier *et al*., 2010; Sharma *et al*., 2021), developing cognitive operational functions across shop floors (e.g., defining objectives, comprehending their environments, and organizing their processes). Real-time predictive analytics, through affordable and robust sensors, can reach time-sensitive decisions, bolstered by machine learning techniques and algorithms, regarding machine, tool, or process failure. Cognitive robots analyze the states of other industrial units in their environment. Industrial automation has indeed redesigned material processing tasks to a significant extent: automation of sensing will technologize a growing proportion of the data processing and decision making undertakings in the factory.

Cognitive capabilities lead to increased flexibility and variability that enable streamlined production (Kumar & Jaiswal, 2021; Li *et al*., 2021a; Perzylo *et al*., 2019; Woo *et al*., 2020; Zhao & Xu, 2010), and thus process planning in smart manufacturing systems has to be robust enough for machine tools and production environments. Real-time collection of production and process data in addition to feedback to operational control are decisive when the information stream between manufacturing techniques is sectioned, necessitating an integrated data pattern to display information. Human-level data processing across cognitive computing, Industrial Internet of Things, and robot learning (Kumar & Jaiswal, 2021; Li *et al*., 2021a; Lyons, 2022a) can connect knowledge categorization and information sharing between smart manufacturing systems. Real-time tangible data assets and big data-driven technologies are pivotal in sustainable product lifecycle management. Data classification is an essential analytical technique across cognitively capable manufacturing sectors for identifying specific patterns throughout the structured and unstructured information (Perzylo *et al*., 2019; Woo *et al*., 2020; Zhao & Xu, 2010) at the shop floor, company, and industry levels. The planning of abstract guidelines of process phases and their demands to executable code takes place when an operational model is leveraged to a manufacturing cell or assembly-line production, and can be determined automatically. Industry 4.0 represents a thoroughly integrated cognitive manufacturing system. Cognitive manufacturing systems can harness semantic capability designations of production resources to coherently redesign operational processes. The layer of abstraction assists in advancing and configuring manufacturing processes autonomous from equipment or software components (Table 3).

Cutting-edge cognitive computing, big data analytics techniques, and Industrial Internet of Things in smart manufacturing systems

Cognitive manufacturing systems can provide increased value and precision in complex operational processes (Krüger *et al*., 2016; Li *et al*., 2015; Palombarini & Martínez, 2012; Siafara *et al*., 2018), attaining elevated quality and efficiency at decreased expenses and diminished production time. Industrial robots harnessed during machining applications can optimize a complementary, flexible, and affordable manufacturing technology in comparison with standard machine tools. Cognitive manufacturing systems can handle unpredicted events and disturbances that perpetually necessitate real-time repair decisions, and thus functionalities such as learning/reasoning abilities and interactive capabilities can reorganize a factory instantaneously. Unsatisfactory precision and unpredictability under heterogeneous configurations of industrial robots constitute main obstacles for harnessing cyber-physical system-based real-time monitoring, artificial intelligence-based decision-making algorithms, and robotic wireless sensor networks (Kliestik *et al*., 2022a; Poliak *et al*., 2022; Sharma *et al*., 2021) in sustainable product lifecycle management. Cognitive systems can deploy artificial intelligence-based decision-making algorithms adequately even without a complete or accurate model. Cognitive system design patterns are instrumental in the robust adjustment of the big data-driven decision-making processes and the perpetual increase in efficiency through knowledge assimilation by analysis of the environment and interpretation for reducing inaccuracies and identifying enhanced operational approaches.

Cognitive manufacturing is pivotal in sustainable Industry 4.0 wireless networks (Chung *et al*., 2019; Din *et al*., 2019; Ferreras-Higuero *et al*., 2020; Hu *et al*., 2016; Ksentini *et al*., 2021) together with blockchain distributed ledger that ensures soundness, safety, and security through mining-based smart data technologies. By leveraging data mining techniques throughout cognitive manufacturing processes, information can be obtained and intrinsic rules are identified: the mining operation assists in the configuration of big data-driven decision-making processes. Artificial intelligence data-driven Internet of Things systems, deep learning-assisted smart process planning, and real-time sensor networks are critical in logistics, equipment, allocation, production, and quality management operations, advancing constantly optimized smart manufacturing systems. Adequate approach of gathering, sharing, and processing thoroughgoing product manufacturing data in the course of machining processes (Balica, 2022; Hawkins, 2022a; Zvarikova *et al.*, 2021) is required for carrying out increased efficiency production. Internet of Things-based machine learning mechanisms can set up ubiquitous connections across wireless nodes, configuring a network that strengthens or stabilizes communications (Dawson, 2022; Kovacova *et al.*, 2022a, 2022b; Rice, 2022) among algorithm-driven sensing devices without human interactions. The increasing advancement of Internet of Things-based decision support systems, cyber-physical production networks, and deep learning-assisted smart process planning and their integration among cloud and fog paradigms have furthered groundbreaking technologies. Industrial robots can be deployed at machining cells for automation feeding and raw material management. A reorganization of tasks to enhance the output performance necessitates a consolidation of the robot behavior, with the aim of optimizing its position precision.

Progresses in deep learning techniques enable image processing algorithms (Ferreras-Higuero *et al.*, 2020; Gordon, 2022; Sharma *et al.*, 2021) to improve themselves autonomously. The extensive deployment of sensors furthers the instantaneous generation and acquisition of data as operational processes take place throughout the manufacturing setting, articulating the transition to real-time data scanning and storage. Advancements in trained cognitive algorithms and deep learning techniques require developments in big data technologies. Machine learning-based analytics, techniques, and algorithms are interpretive technologies (Beckett, 2022; Kovacova *et al.*, 2022a, 2022b; Ksentini *et al.*, 2021) that integrate groundbreaking cognitive capabilities within robots. Machine learning algorithms maintaining the operations of execution technologies (e.g., machines and industrial automation) assimilate knowledge by optimizing their operations in accordance with the outcome of actions, leveraging the entire cognitive and automation capacity of the interpretive and execution technology elements. Manufacturing is going through a paradigmatic transition by integrating and being altered by cognitive technologies (Dawson, 2022; Hawkins, 2022a; Peters, 2022a) by use of product decision-making information systems, cyber-physical system-based real-time monitoring, robotic wireless sensor networks, and Internet of Things smart devices in sustainable product lifecycle management (Table 4).

Cyber-physical systems, big data-driven deep learning, and real-time scheduling algorithms in cognitive manufacturing

Cognitive manufacturing integrates artificial intelligence-based decision-making algorithms, real-time big data analytics, sustainable industrial value creation, and digitized mass production (Ding *et al*., 2021; Dumitrache *et al*., 2019; ElMaraghy & ElMaraghy, 2022; Emmer *et al*., 2018) by leveraging shop floor data as regards design and maintenance, so as to advance, through automatically harnessing assets and equipments, cognitive processes by inspecting information from workflows and environment, consequently leading to resource use optimization. Sustainable manufacturing technologies and systems, together with cognitive digital twins, integrate smart machines. Cognitive technical systems can perceive situations and contexts, determine them, and choose either to use an operational strategy or configure a set of undertakings that tackle aspects of the identified circumstances (Ding *et al*., 2021; Dumitrache *et al*., 2019; Peters, 2022a), enabling the accomplishment of the established objectives. Cognitive systems' practice, record, and learning capacity are decisive in contextualizing unprocessed data as applied meaningful knowledge. Sensorial and auto-diagnosis data have to be harnessed by heterogeneous architectural modules and straightened out in conformity with their consequences, extensiveness, and goal for the identified situation and context. A heterogeneity of measurement tools, approaches, and applications are employed in the manufacturing sector (Emmer *et al*., 2018; Mladineo *et al*., 2022; Zvarikova *et al*., 2021) to set out a certain degree of product quality: a huge volume of devices and processes are deployed in quality management. Cognitive manufacturing typifies cyber-physical production systems. Customer-centered individualized manufactured items can be attained by use of cyber-physical system-based real-time monitoring that has to be integrated into the factory-level production system to further service-oriented shared manufacturing operations.

Cognitive manufacturing systems promptly react to satisfy fluctuating demands and requirements in the shop floor (Casadei *et al*., 2019; Hu *et al*., 2019; Qin & Lu, 2021), across the supply network, and as regards customer needs. Current manufacturing systems are sometimes unsuccessful in aligning with inconstant production environments by altering system infrastructures and production arrangements while preserving robust operational performance. Manufacturing systems should self-optimize production processes (Hu *et al*., 2019; Mladineo *et al*., 2022; Qin & Lu, 2021) to attain adjustable, self-regulating, and error-tolerant fabrication throughout large-scale customization operations. Human–machine collaboration requires cutting-edge cognitive manufacturing control algorithms to constitute shared intelligence. Large-scale customization necessitates responsive and adjustable manufacturing processes (Casadei *et al*., 2019; Ding *et al*., 2021; ElMaraghy & ElMaraghy, 2022) for fabricating personalized products in varying batch proportions and large volumes inexpensively. Artificial intelligence data-driven Internet of Things systems, sustainable Industry 4.0 wireless networks, and cyber-physical system-based real-time monitoring in smart networked factories have been determinants in pushing forwards the technical breakthroughs of intelligent manufacturing. Technological breakthroughs have furthered deep learning-assisted smart process planning, in which cyber-physical contextual services are supplied by use of Internet of Things-based real-time production logistics, digitized mass production, and sustainable industrial big data to articulate smart networked factories.

Industrial Internet of Things-enabled cognitive manufacturing can assist in processing huge volumes of real-time data (Elia & Margherita, 2021; Li *et al*., 2021b; Liu *et al*., 2022) across cyber-physical production systems. Cognitive manufacturing harnesses big data-driven intelligence in the shop floor, empowers industrial production systems with rational and cognitive capabilities, carries out decision-making tasks, and perceives modifications in operational processes. Deep-learning based cognitive technologies can optimize value creation capabilities of organizations that leverage advanced analytics and cyber-physical production systems (Elia & Margherita, 2021; Li *et al*., 2021b; Liu *et al*., 2022), thus developing into cognitive enterprises in terms of technological infrastructure and organizational architecture, integrating smart data and computing processes so as to enhance situational awareness, resilience, agility, and reactivity. Ground-breaking cognitive computing, big data analytics, machine learning algorithms, and Industrial Internet of Things approaches can be deployed to attain on-demand manufacturing-based mass personalization by use of dynamic logistics scheduling and production planning.

Technological upsides in cognitive digitalization can be attained through the integration of artificial intelligence-based decision-making algorithms, Internet of Things smart devices, industrial big data, and real-time process monitoring (Cavallo *et al*., 2021; Chung & Yoo, 2020; Gain, 2021; Penumuru *et al*., 2020) in sustainable product lifecycle management. Cognitive output can improve perceptions as regards a manufactured item, a process or a service, configuring assessable business purposes. Industrial Internet of Things business models and value propositions can harmonize the smart analyses of cognitive output to business purposes, reinforcing and requiring transparency, while providing data-driven goal analyses. Operational indicators facilitate networking among smart things (Cavallo *et al*., 2021; Liu *et al.*, 2022; Qin & Lu, 2021) through artificial intelligence-based decision-making algorithms, cyber-physical process monitoring systems, and real-time sensor networks in sustainable Industry 4.0. Machine tools and Internet of Things-based decision support systems can configure customized behaviors according to consumers' sensations, emotions, and moods, to be consonant with users' states and activities. Machine tools in cyber-physical system-based manufacturing can identify handled materials, implementing specific decisions autonomously. Automated material identification can deploy machine vision and artificial intelligence-based decision-making algorithms to catalyze the cognitive abilities of equipment and material handling devices in smart networked factories (Table 5).

Discussion

This systematic literature review investigates how cognitive decision-making algorithms, mobile sensors and actuators, and predictive maintenance tools are pivotal in cooperative multi-robot systems. Cognitive manufacturing integrates artificial intelligence-based decision-making algorithms, real-time big data analytics, sustainable industrial value creation, and digitized mass production. Cyber-physical contextual services are supplied by use of Internet of Things-based real-time production logistics, digitized mass production, and sustainable industrial big data (Blake, 2022; Kliestik *et al*., 2022b; Rogers & Zvarikova, 2021; Welch, 2021) to articulate smart networked factories.

Significant research has elucidated how cognitive technologies progressively integrate themselves at all levels of the manufacturing enterprises. Machine learning-based analytics, techniques, and algorithms (Androniceanu *et al*., 2021a, 2021b; Grondys & Ślusarczyk, 2022; Mircică, 2020; Valaskova *et al*., 2021) assimilate groundbreaking cognitive capabilities (Beckett, 2022; Kovacova *et al*., 2022a, 2022b; Ksentini *et al*., 2021) within robots. Automation of sensing will technologize a growing proportion of the data processing and decision making undertakings (Androniceanu, 2021; Hawkins, 2022b; Nica *et al*., 2022; Vătămănescu *et al*., 2020) in the factory.

We integrate research developing on how robotic navigation processes deploy visual and spatial intelligence tools, context awareness algorithms, and semantic sensor technologies. Manufacturing integrates and is altered by cognitive technologies (Sharma *et al*., 2021) by use of product decision-making information systems, cyber-physical system-based real-time monitoring, robotic wireless sensor networks, and Internet of Things smart devices (Bailey, 2021; Hudson, 2022; Pelau *et al*., 2021; Vătămănescu *et al*., 2022) in sustainable product lifecycle management. The integration of artificial intelligence data-driven Internet of Things systems and real-time advanced analytics (Krüger *et al*., 2016; Li *et al*., 2015; Palombarini & Martínez, 2012; Siafara *et al*., 2018) has furthered the swift advancement of Internet of Things-based real-time production logistics.

We indicate that autonomous cognitive systems and swarm robots require cloud manufacturing processes, intelligent control algorithms, and image acquisition and processing tools. Deep-learning based cognitive technologies can optimize value creation capabilities (Elia & Margherita, 2021; Li *et al*., 2021b; Liu *et al*., 2022) of organizations that leverage advanced analytics and cyber-physical production systems. Industrial Internet of Things-enabled cognitive manufacturing can assist in processing huge volumes of real-time data (Cavallo *et al*., 2021; Chung & Yoo, 2020; Gain, 2021; Penumuru *et al*., 2020) across cyber-physical production systems.

The findings gathered from our analyses clarify that cognitive capabilities lead to increased flexibility and variability that enable streamlined production. Cognitive manufacturing systems can provide increased value and precision (Barbu *et al*., 2021; Ionescu, 2020; Peters, 2022b; Watson, 2022) in complex operational processes. Artificial intelligence data-driven Internet of Things systems, deep learning-assisted smart process planning, and real-time sensor networks (Altaf *et al*., 2021; Chang *et al*., 2021; Chung *et al*., 2019; Maier *et al*., 2010; Zeba *et al*., 2021; Zheng *et al*., 2021) advance constantly optimized smart manufacturing systems. The integration of artificial intelligence-based decision-making algorithms, Internet of Things smart devices, industrial big data, and real-time process monitoring (Kumar & Jaiswal, 2021; Li *et al*., 2021a; Perzylo *et al*., 2019; Woo *et al*., 2020; Zhao & Xu, 2010) is pivotal in cognitive digitalization.

We show how robots and automated technologies make decisions (Durana *et al*., 2022; Mihăilă & Braniște, 2021; Stone *et al*., 2022) by use of industrial big data analytics (Ding *et al*., 2021; Dumitrache *et al*., 2019; Emmer *et al*., 2018) in Internet of Things-based real-time production logistics, deep learning-assisted smart process planning, and cyber-physical process monitoring systems (Bratu & Sabău, 2022; Lyons, 2022b; Shpak *et al*., 2021; Zvarikova *et al*., 2022) in networked factories.

Conclusions

Relevant research has investigated how cognitive manufacturing systems is developed on sustainable product lifecycle management, Internet of Things-based real-time production logistics, and deep learning-assisted smart process planning, optimizing value creation capabilities and artificial intelligence-based decision-making algorithms. Cognitive robotics leverages imaging and sensing tools, autonomous cyber-physical systems, and mobile sensors and actuators. Artificial intelligence data-driven Internet of Things systems, sustainable industrial big data, and robotic wireless sensor networks can assist in processing huge volumes of real-time data in cognitive digitalization, by leveraging advanced analytics and cyber-physical production systems. Autonomous mobile robot navigation develops on motion control algorithms, predictive maintenance tools, and cloud computing machines. Smart interconnected and autonomous mobile robots integrate dynamic operating systems, image enhancement algorithms, and sensor and actuator devices.

This systematic literature review covers outstanding published peer-reviewed evidence concerning cognitive technologies progressively integrating themselves at all levels of the manufacturing enterprises. Cognitive robotic devices and robotic coordination mechanisms necessitate autonomous navigation systems, swarm intelligence algorithms, and deep reinforcement learning tools in synthetic simulation environments. Product decision-making information systems, deep learning-assisted smart process planning, and Internet of Things smart devices enhance cognitive technologies by processing industrial big data in complex operational processes. Context awareness and visual perception algorithms are instrumental in mobile robotic devices and autonomous robotic systems across smart networked environments. The findings derived from the above analyses clarify that cognitive manufacturing integrates artificial intelligence-based decision-making algorithms, real-time big data analytics, sustainable industrial value creation, and digitized mass production. Deep learning-based image classification algorithms configure autonomous swarm robots and robotic communication systems in terms of remote sensing, path planning, and object recognition. Artificial Intelligence of Things-based cognitive manufacturing networks harness real-time sensor devices, cyber-physical production systems, and automated technologies, increasing value and precision. Cyber-physical manufacturing and mobile context awareness systems articulate cooperative behavior algorithms of mobile swarm robots.

Specific contributions to the literature

This systematic review covers an important topic that has not been investigated until now: artificial intelligence-based decision-making algorithms, Internet of Things sensing networks, and sustainable cyber-physical management systems in big data-driven cognitive manufacturing. Robotic operating systems necessitate remote sensing algorithms, imaging-based navigation technologies, and intuitive decision-making and acoustic environment recognition tools. Motion sensing capabilities, sound recognition systems, and fault diagnosis algorithms are pivotal in networked cloud robotics. Decision support systems, virtual manufacturing modeling and visual navigation tools, and path planning algorithms configure context-aware robotic networks. Connected mobile devices, sensor fusion-based systems, and motion planning algorithms articulate autonomous operational decisions of collaborative robots. Industrial wireless sensor networks, spatial mapping algorithms, and production process modeling and context modeling tools assist mobile robotic systems in dynamic industrial environments.

Our analyses specifically prove that computer vision algorithms, modeling and simulation tools, and sensing and actuating devices enable robotic cooperative behaviors in Industry 4.0-based networked environments. Remote interaction sensors, object tracking algorithms, and intelligent data processing tools further autonomous robotic technologies and manufacturing processes in visual simulation environments. Perception and cognition algorithms, coordinated motion planning and image processing tools, and industrial automation technologies shape cloud and swarm robotics in smart manufacturing management. Space situational awareness and navigation management tools, obstacle detection technologies, and steering control algorithms optimize mobile autonomous robots. Autonomous robotic systems harness visual recognition technologies, environment mapping algorithms, and computational intelligence tools in dynamic unstructured environments.

Limitations and further directions of research

As limitations, by inspecting only sources published in journals indexed in ProQuest, Scopus, and the Web of Science databases between 2010 and 2022, important articles on artificial intelligence-based decision-making algorithms, Internet of Things sensing networks, and sustainable cyber-physical management systems in big data-driven cognitive manufacturing may have been omitted. Subsequent interest should be oriented to how predictive maintenance can assist deep-learning based cognitive technologies in advancing machine learning-based analytics, techniques, and algorithms in networked factories. The scope of our research does not advance how Industrial Internet of Things-enabled cognitive manufacturing, cyber-physical system-based real-time monitoring, and industrial big data analytics articulate smart networked factories. Future research should investigate the relationship between cyber-physical process monitoring systems, Internet of Things smart devices, real-time process monitoring in assimilating groundbreaking cognitive capabilities.

Practical implications

Image acquisition devices, context recognition tools, and computer vision algorithms enable autonomous visual object detection and sensor data fusion in cloud and networked robotics. Visual perception algorithms, remote sensing technologies, and localization and navigation tools further cloud-based production processes related to operating robotic systems in synthetic simulation environments. Deep learning-based image processing algorithms, smart sensor devices, and ambient intelligence tools shape swarm robotic systems across mobile edge computing environments. Sensing device capabilities, motion control algorithms, and context awareness tools optimize networked robotic systems. Robotic cooperation systems harness location identification tools, data processing algorithms, and vision sensing technology across augmented operating environments. Cloud networked robots and computing technologies deploy spatial mapping algorithms, smart interconnected devices, and autonomous and collaborative robots. Autonomous robotic systems leverage collision avoidance algorithms, signal processing tools, and machine perception technologies. Mobile robot movements develop on computer vision capabilities, object recognition algorithms, and interconnected virtual devices. Robotic agent behaviors integrate distributed sensor networks, predictive geospatial modeling tools, and environment mapping algorithms. Networked robots require geolocation data intelligence and visual modeling tools, context awareness algorithms, and distributed sensing technologies.

References

Altaf, A., Abbas, H., Iqbal, F., Khan, F. A., Rubab, S., & Derhab, A. (2021). Context-oriented trust computation model for Industrial Internet of Things. *Computers & Electrical Engineering*, *92*, 107123. doi: 10.1016/j.compeleceng.2021.107123.

Andronie, M., Lăzăroiu, G., Iatagan, M., Uță, C., Ștefănescu, R., & Cocoșatu, M. (2021a). Artificial intelligence-based decision-making algorithms, Internet of Things sensing networks, and deep learning-assisted smart process management in cyber-physical production systems. *Electronics*, *10*(20), 2497. doi: 10.3390/electronics10202497.

Andronie, M., Lăzăroiu, G., Ștefănescu, R., Uță, C., & Dijmărescu, I. (2021b). Sustainable, smart, and sensing technologies for cyber-physical manufacturing systems: a systematic literature Review. *Sustainability*, *13*(10), 5495. doi: 10.3390/su13105495.

Andronie, M., Lăzăroiu, G., Iatagan, M., Hurloiu, I., & Dijmărescu, I. (2021c). Sustainable cyber-physical production systems in big data-driven smart urban economy: a systematic literature review. *Sustainability*, *13*(2), 751. doi: 10.3390/su13020751.

Androniceanu, A., Nica, E., Georgescu, I., & Sabie, O. M. (2021a). The influence of the ICT on the control of corruption in public administrations of the EU member states: a comparative analysis based on panel data. *Administratie si Management Public*, *37*, 41–59. doi: 10.24818/amp/2021.37-03.

Androniceanu, A.-M., Căplescu, R. D., Tvaronavičienė, M, & Dobrin, C. (2021b). The interdependencies between economic growth, energy consumption and pollution in Europe. *Energies*, *14*(9), 2577. doi: 10.3390/en14092577.

Androniceanu, A. (2021). Transparency in public administration as a challenge for a good democratic governance. *Administratie si Management Public*, *36*, 149–164. doi: 10.24818/amp/2021.36-09.

Bailey, L. (2021). The digital fabric of reproductive technologies: fertility, pregnancy, and menstrual cycle tracking apps. *Journal of Research in Gender Studies*, *11*(2), 126–138. doi: 10.22381/JRGS11220219.

Balica, R.-Ș. (2022). Machine and deep learning technologies, wireless sensor networks, and virtual simulation algorithms in digital twin cities. *Geopolitics, History, and International Relations*, *14*(1), 59–74. doi: 10.22381/GHIR14120224.

Barbu, C. M., Florea, D. L., Dabija, D. C., & Barbu, M. C. R. (2021). Customer experience in Fintech. *Journal of Theoretical and Applied Electronic Commerce Research*, *16*(5), 1415–1433. doi: 10.3390/jtaer16050080.

Beckett, S. (2022). Machine and deep learning technologies, location tracking and obstacle avoidance algorithms, and cognitive wireless sensor networks in intelligent transportation planning and engineering. *Contemporary Readings in Law and Social Justice*, *14*(1), 41–56. doi: 10.22381/CRLSJ14120223.

Blake, R. (2022). Metaverse technologies in the virtual economy: deep learning computer vision algorithms, blockchain-based digital assets, and immersive shared worlds. *Smart Governance*, *1*(1), 35–48. doi: 10.22381/sg1120223.

Bratu, S., & Sabău, R. I. (2022). Digital commerce in the immersive metaverse environment: cognitive analytics management, real-time purchasing data, and seamless connected shopping experiences. *Linguistic and Philosophical Investigations*, *21*, 170–186. doi: 10.22381/lpi21202211.

Casadei, R., Fortino, G., Pianini, D., Russo, W., Savaglio, C., & Viroli, M. (2019). A development approach for collective opportunistic edge-of-things services. *Information Sciences*, *498*, 154–169. doi: 10.1016/j.ins.2019.05.058.

Cavallo, F., Semeraro, F., Mancioppi, G., Betti, S., & Fiorini, L. (2021). Mood classification through physiological parameters. *Journal of Ambient Intelligence and Humanized Computing*, *12*, 4471–4484. doi: 10.1007/s12652-019-01595-6

Chang, Z., Liu, S., Xiong, X., Cai, Z., & Tu, G. (2021). A survey of recent advances in edge-computing-powered artificial Intelligence of Things. *IEEE Internet of Things Journal*, *8*(18), 13849–13875. doi: 10.1109/JIOT.2021.3088875.

Chung, K., Yoo, H., Choe, D., & Jung, H. (2019). Blockchain network based topic mining process for cognitive manufacturing. *Wireless Personal Communications*, *105*, 583–597. doi: 10.1007/s11277-018-5979-8.

Chung, K., & Yoo, H. (2020). Edge computing health model using P2P-based deep neural networks. *Peer-to-Peer Networking and Applications*, *13*, 694–703. doi: 10.1007/s12083-019-00738-y

Cug, J., Suler, P., & Taylor, E. (2022). Digital twin-based cyber-physical production systems in immersive 3D environments: virtual modeling and simulation tools, spatial data visualization techniques, and remote sensing technologies. *Economics, Management, and Financial Markets*, *17*(2), 82–96. doi: 10.22381 /emfm17220225.

Dawson, A. (2022). Data-driven consumer engagement, virtual immersive shopping experiences, and blockchain-based digital assets in the retail metaverse. *Journal of Self-Governance and Management Economics, 10*(2), 52–66. doi: 10.22381/jsme10220224.

Din, I. U., Guizani, M., Rodrigues, J. J. P. C., Hassan, S., & Korotaev, V. V. (2019). Machine learning in the Internet of Things: designed techniques for smart cities. *Future Generation Computer Systems*, *100*, 826–843. doi: 10.1016/j.future.2019.04.017.

Ding, K., Zhang, Y., Chan, F. T. S., Zhang, C., Lv, J., Liu, Q., Leng, J., & Fue, H. (2021). A cyber-physical production monitoring service system for energy-aware collaborative production monitoring in a smart shop floor. *Journal of Cleaner Production*, *297*, 126599. doi: 10.1016/j.jclepro.2021.126599.

Dumitrache, I., Caramihai, S. I., Moisescu, M. A., & Sacala, I. S. (2019). Neuro-inspired framework for cognitive manufacturing control. *IFAC-PapersOnLine*, *52*, 910–915. doi: 10.1016/j.ifacol.2019.11.311.

Durana, P., Krulicky, T., & Taylor, E. (2022). Working in the metaverse: virtual recruitment, cognitive analytics management, and immersive visualization systems. *Psychosociological Issues in Human Resource Management*, *10*(1), 135–148. doi: 10.22381/pihrm101202210.

Elia, G., & Margherita, A. (2021). A conceptual framework for the cognitive enterprise: pillars, maturity, value drivers. *Technology Analysis & Strategic Management*, *34*(4), 377–389. doi: 10.1080/09537325.2021.1901874.

ElMaraghy, H., & ElMaraghy, W. (2022). Adaptive cognitive manufacturing system (ACMS) – a new paradigm. *International Journal of Production Research*, *60*(24), 7436–7449. doi: 10.1080/00207543.2022.2078248.

Emmer, C., Hofmann, T. M., Schmied, T., Stjepandić, J., & Strietzel, M. (2018). A neutral approach for interoperability in the field of 3D measurement data management. *Journal of Industrial Information Integration*, *12*, 47–56. doi: 10.1016/j.jii.2018.01.006.

Ferreras-Higuero, E., Leal-Muñoz, E., García de Jalón, J., Chacón, E., & Vizán, A. (2020). Robot-process precision modelling for the improvement of productivity in flexible manufacturing cells. *Robotics and Computer-Integrated Manufacturing*, *65*, 101966. doi: 10.1016/j.rcim.2020.101966.

Gain, U. (2021). Applying frameworks for cognitive services in IIoT. *Journal of Systems Science and Systems Engineering*, *30*, 59–84. doi: 10.1007/s11518-021-5480-x.

Gordon, S. (2022). Computer vision algorithms, vehicle navigation and remote sensing technologies, and smart traffic planning and analytics in urban transportation systems. *Contemporary Readings in Law and Social Justice*, *14*(1), 9–24. doi: 10.22381/CRLSJ14120221.

Grondys, K., & Ślusarczyk, O. (2022). Passenger potential and the operating result of the public transport organization. *Administratie si Management Public*, *38*, 104–119. doi: 10.24818/amp/2022.38-06.

Hawkins, M. (2022a). Virtual employee training and skill development, workplace technologies, and deep learning computer vision algorithms in the immersive metaverse environment. *Psychosociological Issues in Human Resource Management*, *10*(1), 106–120. doi: 10.22381/pihrm10120228.

Hawkins, M. (2022b). Metaverse live shopping analytics: retail data measurement tools, computer vision and deep learning algorithms, and decision intelligence and modeling. *Journal of Self-Governance and Management Economics*, *10*(2), 22–36. doi: 10.22381/jsme10220222.

Hu, P., Han, Z., Fu, H., & Han, D. (2016). Architecture and implementation of closed-loop machining system based on open STEP-NC controller. *International Journal of Advanced Manufacturing Technology*, *83*, 1361–1375. doi: 10.1007/s00170-015-7631-z.

Hu, L., Miao, Y., Wu, G., Hassan, M. M., & Humar, I. (2019). iRobot-Factory: an intelligent robot factory based on cognitive manufacturing and edge computing. *Future Generation Computer Systems*, *90*, 569–577. doi: 10.1016/j.future.2018.08.006.

Hudson, J. (2022). Internet of Medical Things-driven remote monitoring systems, big healthcare data analytics, and wireless body area networks in COVID-19 detection and diagnosis. *American Journal of Medical Research*, *9*(1), 81–96. doi: 10.22381/ajmr9120226.

Ionescu, L. (2020). Digital data aggregation, analysis, and infrastructures in FinTech operations. *Review of Contemporary Philosophy*, *19*, 92–98. doi: 10.22381/RCP19202010.

Kliestik, T., Poliak, M., & Popescu, G. H. (2022a). Digital twin simulation and modeling tools, computer vision algorithms, and urban sensing technologies in immersive 3D environments. *Geopolitics, History, and International Relations*, *14*(1), 9–25. doi: 10.22381/GHIR14120221.

Kliestik, T., Novak, A., & Lăzăroiu, G. (2022b). Live shopping in the metaverse: Visual and spatial analytics, cognitive artificial intelligence techniques and algorithms, and immersive digital simulations. *Linguistic and Philosophical Investigations*, *21*, 187–202. doi: 10.22381/lpi21202212.

Kovacova, M., Machova, V., & Bennett, D. (2022a). Immersive extended reality technologies, data visualization tools, and customer behavior analytics in the metaverse commerce. *Journal of Self-Governance and Management Economics*, *10*(2), 7–21. doi: 10.22381/jsme10220221.

Kovacova, M., Novak, A., Machova, V., & Carey, B. (2022b). 3D virtual simulation technology, digital twin modeling, and geospatial data mining in smart sustainable city governance and management. *Geopolitics, History, and International Relations*, *14*(1), 43–58. doi: 10.22381/GHIR14120223.

Krüger, J., Zhao, H., Reis de Ascencao, G., Jacobi, P., Surdilovic, D., Schöll, S., & Polley, W. (2016). Concept of an offline correction method based on historical data for milling operations using industrial robots. *Production Engineering*, *10*, 409–420. doi: 10.1007/s11740-016-0686-3.

Ksentini, A., Jebalia, M., Tabbane, S. (2021). IoT/Cloud-enabled smart services: a review on QoS requirements in fog environment and a proposed approach based on priority classification technique. *International Journal of Communication Systems*, *34*, e4269. doi: 10.1002/dac.4269.

Kumar, A., & Jaiswal, A. (2021). A deep swarm-optimized model for leveraging industrial data analytics in cognitive manufacturing. *IEEE Transactions on Industrial Informatics*, *17*, 2938–2946. doi: 10.1109/TII.2020.3005532.

Lăzăroiu, G., Pera, A., Ștefănescu-Mihăilă, R. O., Mircică, N., & Neguriță, O. (2017). Can neuroscience assist us in constructing better patterns of economic decision-making? *Frontiers in Behavioral Neuroscience*, *11*, 188. doi: 10.3389/fnbeh.2017.00188.

Lăzăroiu, G., Andronie, M., Iatagan, M., Geamănu, M., Ștefănescu, R., & Dijmărescu, I. (2022). Deep learning-assisted smart process planning, robotic wireless sensor networks, and geospatial big data management algorithms in the Internet of Manufacturing Things. *ISPRS International Journal of Geo-Information*, *11*(5), 277. doi: 10.3390/ijgi11050277.

Li, Y., Liu, C., Gao, J. X., & Shen, W. (2015). An integrated feature-based dynamic control system for on-line machining, inspection and monitoring. *Integrated Computer-Aided Engineering*, *22*, 187–200. doi: 10.3233/ICA-150483.

Li, S., Wang, R., Zheng, P., & Wang, L. (2021a). Towards proactive human–robot collaboration: a foreseeable cognitive manufacturing paradigm. *Journal of Manufacturing Systems*, *60*, 547–552. doi: 10.1016/j.jmsy.2021.07.017.

Li, X., Zheng, P., Bao, J., Gao, L., & Xu, X. (2021b). Achieving cognitive mass personalization via the self-X cognitive manufacturing network: an industrial-knowledge-graph- and graph-embedding-enabled pathway. *Engineering*. Advance online publication. doi: 10.1016/j.eng.2021.08.018.

Liu, M., Li, X., Li, J., Liu, Y., Zhou, B., & Bao, J. (2022). A knowledge graph-based data representation approach for IIoT-enabled cognitive manufacturing. *Advanced Engineering Informatics*, *51*, 101515. doi: 10.1016/j.aei.2021.1015 15.

Lyons, N. (2022a). Deep learning-based computer vision algorithms, immersive analytics and simulation software, and virtual reality modeling tools in digital twin-driven smart manufacturing. *Economics, Management, and Financial Markets*, *17*(2), 67–81. doi: 10.22381/emfm17220224.

Lyons, N. (2022b). Talent acquisition and management, immersive work environments, and machine vision algorithms in the virtual economy of the metaverse. *Psychosociological Issues in Human Resource Management*, *10*(1), 121–134. doi: 10.22381/pihrm10120229.

Maier, P., Sachenbacher, M., Rühr, T., & Kuhn, L. (2010). Automated plan assessment in cognitive manufacturing. *Advanced Engineering Informatics*, *24*, 308–319. doi: 10.1016/j.aei.2010.05.015

Michalkova, L., Machova, V., & Carter, D. (2022). Digital twin-based product development and manufacturing processes in virtual space: data visualization tools and techniques, cloud computing technologies, and cyber-physical production systems. *Economics, Management, and Financial Markets*, *17*, 37–51. doi: 10.22381/emfm17220222.

Mihăilă, R., & Braniște, L. (2021). Digital semantics of beauty apps and filters: Big data-driven facial retouching, aesthetic self-monitoring devices, and augmented reality-based body-enhancing technologies. *Journal of Research in Gender Studies*, *11*(2), 100–112. doi: 10.22381/JRGS11220217.

Mircică, N. (2020). Restoring public trust in digital platform operations: machine learning algorithmic structuring of social media content. *Review of Contemporary Philosophy*, *19*, 85–91. doi: 10.22381/RCP1920209.

Mladineo, M., Crnjac Zizic, M., Aljinovic, A., & Gjeldum, N. (2022). Towards a knowledge-based cognitive system for industrial application: case of personalized products. *Journal of Industrial Information Integration*, *27*, 100284. doi: 10.1016/j.jii.2021.100284.

Nagy, M., & Lăzăroiu, G. (2022). Computer vision algorithms, remote sensing data fusion techniques, and mapping and navigation tools in the Industry 4.0-based Slovak automotive sector. *Mathematics*, *10*(19), 3543. doi: 10.3390/math1019 3543.

Nica, E., Kliestik, T., Valaskova, K., & Sabie, O.-M. (2022). The economics of the metaverse: immersive virtual technologies, consumer digital engagement, and augmented reality shopping experience. *Smart Governance*, *1*(1), 21–34. doi: 10.22381/sg1120222.

Palombarini, J., & Martínez, E. (2012). SmartGantt – an intelligent system for real time rescheduling based on relational reinforcement learning. *Expert Systems with Applications*, *39*, 10251–10268. doi: 10.1016/j.eswa.2012.02.176.

Pelau, C., Dabija, D.-C., & Ene, I. (2021). What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry. *Computers in Human Behavior*, *122*, 106855. doi: 10.1016/j.ch b.2021.106855.

Penumuru, D. P., Muthuswamy, S., & Karumbu, P. (2020). Identification and classification of materials using machine vision and machine learning in the context of industry 4.0. *Journal of Intelligent Manufacturing*, *31*, 1229–1241. doi: 10.1007/s10845-019-01508-6.

Perzylo, A., Grothoff, J., Lucio, L., Weser, M., Malakuti, S., Venet, P., Aravantinos, V., & Deppe, T. (2019). Capability-based semantic interoperability of manufacturing resources: A BaSys 4.0 perspective. *IFAC-PapersOnLine*, *52*, 1590–1596. doi: 10.1016/j.ifacol.2019.11.427.

Peters, E. (2022a). Big geospatial data analytics, connected vehicle technologies, and visual perception and sensor fusion algorithms in smart transportation networks. *Contemporary Readings in Law and Social Justice*, *14*(1), 73–88. doi: 10.22381/CRLSJ14120225.

Peters, M. A. (2022b). A post-Marxist reading of the knowledge economy: open knowledge production, cognitive capitalism, and knowledge socialism. *Analysis and Metaphysics*, *21*, 7–23. doi: 10.22381/am2120221.

Poliak, M., Jurecki, R., & Buckner, K. (2022). Autonomous vehicle routing and navigation, mobility simulation and traffic flow prediction tools, and deep learning object detection technology in smart sustainable urban transport systems. *Contemporary Readings in Law and Social Justice*, *14*(1), 25–40. doi: 10.22381/CRLSJ14120222.

Qin, Z., & Lu, Y. (2021). Self-organizing manufacturing network: a paradigm towards smart manufacturing in mass personalization. *Journal of Manufacturing Systems*, *60*, 35–47. doi: 10.1016/j.jmsy.2021.04.016

Rice, L. (2022). Digital twins of smart cities: spatial data visualization tools, monitoring and sensing technologies, and virtual simulation modeling. *Geopolitics, History, and International Relations*, *14*(1), 26–42. doi: 10.22381/GHIR1412 0222.

Robinson, R. (2022). Digital twin modeling in virtual enterprises and autonomous manufacturing systems: deep learning and neural network algorithms, immersive visualization tools, and cognitive data fusion techniques. *Economics, Management, and Financial Markets*, *17*(2), 52–66. doi: 10.22381/emfm1722 0223.

Rogers, S., & Zvarikova, K. (2021). Big data-driven algorithmic governance in sustainable smart manufacturing: robotic process and cognitive automation technologies. *Analysis and Metaphysics*, *20*, 130–144. doi: 10.22381/am2020 219.

Sharma, A., Zhang, Z., & Rai, R. (2021). The interpretive model of manufacturing: a theoretical framework and research agenda for machine learning in manufacturing. *International Journal of Production Research*, *59*, 4960–4994. doi: 10.1080/00207543.2021.1930234.

Shpak, N., Kulyniak, I., Gvozd, M., Pyrog, O., & Sroka, W. (2021). Shadow economy and its impact on the public administration: aspects of financial and economic security of the country's industry. *Administratie si Management Public*, *36*, 81–101. doi: 10.24818/amp/2021.36-05.

Siafara, L. C., Kholerdi, H., Bratukhin, A., Taherinejad, N., & Jantsch, A. (2018). SAMBA – an architecture for adaptive cognitive control of distributed cyber-physical production systems based on its self-awareness. *E & i Elektrotechnik und Informationstechnik*, *135*, 270–277. doi: 10.1007/s00502-018-0614-7.

Stone, D., Michalkova, L., & Machova, V. (2022). Machine and deep learning techniques, body sensor networks, and Internet of Things-based smart healthcare systems in COVID-19 remote patient monitoring. *American Journal of Medical Research*, *9*(1), 97–112. doi: 10.22381/ajmr9120227.

Valaskova, K., Androniceanu, A-M., Zvarikova, K., & Olah, J. (2021). Bonds between earnings management and corporate financial stability in the context of the competitive ability of enterprises. *Journal of Competitiveness*, *13*(4), 167–184. doi: 10.7441/joc.2021.04.10.

Valaskova, K., Nagy, M., Zabojnik, S., & Lăzăroiu, G. (2022). Industry 4.0 wireless networks and cyber-physical smart manufacturing systems as accelerators of value-added growth in Slovak exports. *Mathematics*, *10*(14), 2452. doi: 10.3390/math10142452.

Vătămănescu, E.-M., Alexandru, V.-A., Mitan, A., & Dabija, D.-C. (2020). From the deliberate managerial strategy towards international business performance: a psychic distance vs. global mindset approach. *Systems Research and Behavioral Science*, *37*(2), 374–387. doi: 10.1002/sres.2658.

Vătămănescu, E.-M., Brătianu, C., Dabija, D.-C., & Popa, S. (2022). Capitalizing online knowledge networks: from individual knowledge acquisition towards organizational achievements. *Journal of Knowledge Management*. Advance online publication. doi: 10.1108/JKM-04-2022-0273.

Watson, R. (2022). Tradeable digital assets, immersive extended reality technologies, and blockchain-based virtual worlds in the metaverse economy. *Smart Governance*, *1*(1), 7–20. doi: 10.22381/sg1120221.

Welch, H. (2021). Algorithmically monitoring menstruation, ovulation, and pregnancy by use of period and fertility tracking apps. *Journal of Research in Gender Studies*, *11*(2), 113–125. doi: 10.22381/JRGS11220218.

Woo, W-S., Kim, E-J., Jeong, H-I., & Lee, C.-M. (2020). Laser-assisted machining of Ti-6Al-4V fabricated by DED additive manufacturing. *International Journal of Precision Engineering and Manufacturing-Green Technology*, *7*, 559–572. doi: 10.1007/s40684-020-00221-7.

Zeba, G., Dabić, M., Čičak, M., Daim, T., & Yalcin, H. (2021). Technology mining: artificial intelligence in manufacturing. *Technological Forecasting and Social Change*, *171*, 120971. doi: 10.1016/j.techfore.2021.120971.

Zhao, Y. F., & Xu, X. (2010). Enabling cognitive manufacturing through automated on-machine measurement planning and feedback. *Advanced Engineering Informatics*, *24*, 269–284. doi: 10.1016/j.aei.2010.05.009.

Zheng, P., Xia, L., Li, C., Li, X., & Liu, B. (2021). Towards Self-X cognitive manufacturing network: an industrial knowledge graph-based multi-agent reinforcement learning approach. *Journal of Manufacturing Systems*, *61*, 16–26. doi: 10.1016/j.jmsy.2021.08.002.

Zvarikova, K., Rowland, M., & Krulicky, T. (2021). Sustainable Industry 4.0 wireless networks, smart factory performance, and cognitive automation in cyber-physical system-based manufacturing. *Journal of Self-Governance and Management Economics*, *9*(4), 9–21. doi: 10.22381/jsme9420211.

Zvarikova, K., Frajtova Michalikova, K., & Rowland, M. (2022). Retail data measurement tools, cognitive artificial intelligence algorithms, and metaverse live shopping analytics in immersive hyper-connected virtual spaces. *Linguistic and Philosophical Investigations*, *21*, 9–24. doi: 10.22381/lpi2120221.

Annex

Table 1. Topics and types of paper identified and selected

Topic	Identified	Selected
cognitive Industrial Internet of Things	39	8
cognitive automation	53	7
cognitive manufacturing systems	74	10
cognitively-enhanced machine	47	8
cognitive technology-driven automation	41	6
cognitive computing technologies	42	6
cognitive technologies	48	6
Type of paper		
original research	253	50
review	24	1
conference proceedings	37	0
book	16	0
editorial	14	0

Note: Some topics overlap.

Table 2. General synopsis of evidence concerning inspected topics and descriptive outcomes (research findings)

The processing of data has been computerized by the integration of software programs for material demand and inventory planning, industrial big data analytics, Internet of Things-based real-time production logistics, and robotic process automation.	Cug *et al.*, 2022; Michalkova *et al.*, 2022; Sharma *et al.*, 2021;
Developments in sensor technologies are optimizing both the scope and scale of information that can be acquired in digital form. Storing big data quantities is essential for adequately training machine learning algorithms.	Robinson, 2022; Kumar & Jaiswal, 2021; Sharma *et al.*, 2021
In a cognitive industrial unit, product manufacturing is robotically planned and itemized, harnessing a knowledge base configuring component capabilities and processes of the shop floor.	Altaf *et al.*, 2021; Chang *et al.*, 2021; Maier *et al.*, 2010; Zeba *et al.*, 2021; Zheng *et al.*, 2021
Cyber-physical systems, big data-driven deep learning, and real-time scheduling algorithms articulate cognitive manufacturing. Internet of Things has developed a thoroughly networked world driven by heterogeneous wireless sensors producing massive volumes of data in various fields and applications.	Chang *et al.*, 2021; Michalkova *et al.*, 2022; Perzylo *et al.*, 2019
Smart manufacturing systems are progressively equipped with perceptive capabilities by use of cutting-edge cognitive computing, big data analytics techniques, and Industrial Internet of Things.	Lyons, 2022a; Robinson, 2022; Sharma *et al.*, 2021;
Machines are getting considerably harmonized with sensors and interpretation algorithms, developing cognitive operational functions across shop floors (e.g., defining objectives, comprehending their environments, and organizing their processes).	Cug *et al.*, 2022; Maier *et al.*, 2010; Sharma *et al.*, 2021
Cognitive capabilities lead to increased flexibility and variability that enable streamlined production, and thus process planning in smart manufacturing systems has to be robust enough for machine tools and production environments.	Kumar & Jaiswal, 2021; Li *et al.*, 2021a; Perzylo *et al.*, 2019; Woo *et*

Table 2. Continued

	al., 2020; Zhao & Xu, 2010
Human-level data processing across cognitive computing, Industrial Internet of Things, and robot learning can connect knowledge categorization and information sharing between smart manufacturing systems.	Kumar & Jaiswal, 2021; Li *et al.*, 2021a; Lyons, 2022a
Data classification is an essential analytical technique across cognitively capable manufacturing sectors for identifying specific patterns throughout the structured and unstructured information at the shop floor, company, and industry levels.	Perzylo *et al.*, 2019; Woo *et al.*, 2020; Zhao & Xu, 2010
Cognitive manufacturing systems can provide increased value and precision in complex operational processes, attaining elevated quality and efficiency at decreased expenses and diminished production time.	Krüger *et al.*, 2016; Li *et al.*, 2015; Palombarini & Martínez, 2012; Siafara *et al.*, 2018
Unsatisfactory precision and unpredictability under heterogeneous configurations of industrial robots constitute main obstacles for harnessing cyber-physical system-based real-time monitoring, artificial intelligence-based decision-making algorithms, and robotic wireless sensor networks in sustainable product lifecycle management.	Kliestik *et al.*, 2022a; Poliak *et al.*, 2022; Sharma *et al.*, 2021
Cognitive manufacturing is pivotal in sustainable Industry 4.0 wireless networks together with blockchain distributed ledger that ensures soundness, safety, and security through mining-based smart data technologies.	Chung *et al.*, 2019; Din *et al.*, 2019; Ferreras-Higuero *et al.*, 2020; Hu *et al.*, 2016; Ksentini *et al.*, 2021
Adequate approach of gathering, sharing, and processing thoroughgoing product manufacturing data in the course of machining processes is required for carrying out increased efficiency production.	Balica, 2022; Hawkins, 2022a; Zvarikova *et al.*, 2021
Internet of Things-based machine learning mechanisms can set up ubiquitous connections across wireless nodes, configuring a network that strengthens or stabilizes communications among algorithm-driven sensing devices without human interactions.	Dawson, 2022; Kovacova *et al.*, 2022a, b; Rice, 2022
Progresses in deep learning techniques enable image processing algorithms to improve themselves autonomously. Advancements in trained cognitive algorithms and deep learning techniques require developments in big data technologies.	Ferreras-Higuero *et al.*, 2020; Gordon, 2022; Sharma *et al.*, 2021;
Machine learning-based analytics, techniques, and algorithms are interpretive technologies that integrate groundbreaking cognitive capabilities within robots.	Beckett, 2022; Kovacova *et al.*, 2022a, b; Ksentini *et al.*, 2021
Manufacturing is going through a paradigmatic transition by integrating and being altered by cognitive technologies by use of product decision-making information systems, cyber-physical system-based real-time monitoring, robotic wireless sensor networks, and Internet of Things smart devices in sustainable product lifecycle management.	Dawson, 2022; Hawkins, 2022a; Peters, 2022a
Cognitive manufacturing integrates artificial intelligence-based decision-making algorithms, real-time big data analytics, sustainable industrial value creation, and digitized mass production by leveraging shop floor data as regards design and maintenance, so as to advance, through automatically harnessing assets and equipments, cognitive processes by inspecting information from workflows and environment, consequently leading to resource use optimization.	Ding *et al.*, 2021; Dumitrache *et al.*, 2019; ElMaraghy & ElMaraghy, 2022; Emmer *et al.*, 2018

Table 2. Continued

Cognitive technical systems can perceive situations and contexts, determine them, and choose either to use an operational strategy or configure a set of undertakings that tackle aspects of the identified circumstances, enabling the accomplishment of the established objectives.	Ding *et al*., 2021; Dumitrache *et al*., 2019; Peters, 2022a
A heterogeneity of measurement tools, approaches, and applications are employed in the manufacturing sector to set out a certain degree of product quality: a huge volume of devices and processes are deployed in quality management.	Emmer *et al*., 2018; Mladineo *et al*., 2022; Zvarikova *et al*., 2021
Cognitive manufacturing systems promptly react to satisfy fluctuating demands and requirements in the shop floor, across the supply network, and as regards customer needs.	Casadei *et al*., 2019; Hu *et al*., 2019; Qin & Lu, 2021
Manufacturing systems should self-optimize production processes to attain adjustable, self-regulating, and error-tolerant fabrication throughout large-scale customization operations.	Hu *et al*., 2019; Mladineo *et al*., 2022; Qin & Lu, 2021;
Large-scale customization necessitates responsive and adjustable manufacturing processes for fabricating personalized products in varying batch proportions and large volumes inexpensively.	Casadei *et al*., 2019; Ding *et al*., 2021; ElMaraghy & ElMaraghy, 2022
Industrial Internet of Things-enabled cognitive manufacturing can assist in processing huge volumes of real-time data across cyber-physical production systems.	Elia & Margherita, 2021; Li *et al*., 2021b; Liu *et al*., 2022
Deep-learning based cognitive technologies can optimize value creation capabilities of organizations that leverage advanced analytics and cyber-physical production systems, thus developing into cognitive enterprises in terms of technological infrastructure and organizational architecture, integrating smart data and computing processes so as to enhance situational awareness, resilience, agility, and reactivity.	Elia & Margherita, 2021; Li *et al*., 2021b; Liu *et al*., 2022
Technological upsides in cognitive digitalization can be attained through the integration of artificial intelligence-based decision-making algorithms, Internet of Things smart devices, industrial big data, and real-time process monitoring in sustainable product lifecycle management.	Cavallo *et al*., 2021; Chung & Yoo, 2020; Gain, 2021; Penumuru *et al*., 2020
Operational indicators facilitate networking among smart things through artificial intelligence-based decision-making algorithms, cyber-physical process monitoring systems, and real-time sensor networks in sustainable Industry 4.0.	Cavallo *et al*., 2021; Liu *et al*., 2022; Qin & Lu, 2021

Table 3. Synopsis of evidence regarding debated topics and descriptive results (research findings)

The processing of data has been computerized by the integration of software programs for material demand and inventory planning, industrial big data analytics, Internet of Things-based real-time production logistics, and robotic process automation.	Cug *et al*., 2022; Michalkova *et al*., 2022; Sharma *et al*., 2021;
Developments in sensor technologies are optimizing both the scope and scale of information that can be acquired in digital form. Storing big data quantities is essential for adequately training machine learning algorithms.	Robinson, 2022; Kumar & Jaiswal, 2021; Sharma *et al*., 2021

Table 3. Continued

In a cognitive industrial unit, product manufacturing is robotically planned and itemized, harnessing a knowledge base configuring component capabilities and processes of the shop floor.	Altaf *et al*., 2021; Chang *et al*., 2021; Maier *et al*., 2010; Zeba *et al*., 2021; Zheng *et al*., 2021
Cyber-physical systems, big data-driven deep learning, and real-time scheduling algorithms articulate cognitive manufacturing. Internet of Things has developed a thoroughly networked world driven by heterogeneous wireless sensors producing massive volumes of data in various fields and applications.	Chang *et al*., 2021; Michalkova *et al*., 2022; Perzylo *et al*., 2019
Smart manufacturing systems are progressively equipped with perceptive capabilities by use of cutting-edge cognitive computing, big data analytics techniques, and Industrial Internet of Things.	Lyons, 2022a; Robinson, 2022; Sharma *et al*., 2021;
Machines are getting considerably harmonized with sensors and interpretation algorithms, developing cognitive operational functions across shop floors (e.g., defining objectives, comprehending their environments, and organizing their processes).	Cug *et al*., 2022; Maier *et al*., 2010; Sharma *et al*., 2021
Cognitive capabilities lead to increased flexibility and variability that enable streamlined production, and thus process planning in smart manufacturing systems has to be robust enough for machine tools and production environments.	Kumar & Jaiswal, 2021; Li *et al*., 2021a; Perzylo *et al*., 2019; Woo *et al*., 2020; Zhao & Xu, 2010
Human-level data processing across cognitive computing, Industrial Internet of Things, and robot learning can connect knowledge categorization and information sharing between smart manufacturing systems.	Kumar & Jaiswal, 2021; Li *et al*., 2021a; Lyons, 2022a
Data classification is an essential analytical technique across cognitively capable manufacturing sectors for identifying specific patterns throughout the structured and unstructured information at the shop floor, company, and industry levels.	Perzylo *et al*., 2019; Woo *et al*., 2020; Zhao & Xu, 2010

Table 4. Synopsis of evidence regarding debated topics and descriptive results (research findings)

Cognitive manufacturing systems can provide increased value and precision in complex operational processes, attaining elevated quality and efficiency at decreased expenses and diminished production time.	Krüger *et al*., 2016; Li *et al*., 2015; Palombarini & Martínez, 2012; Siafara *et al*., 2018
Unsatisfactory precision and unpredictability under heterogeneous configurations of industrial robots constitute main obstacles for harnessing cyber-physical system-based real-time monitoring, artificial intelligence-based decision-making algorithms, and robotic wireless sensor networks in sustainable product lifecycle management.	Kliestik *et al*., 2022a; Poliak *et al*., 2022; Sharma *et al*., 2021
Cognitive manufacturing is pivotal in sustainable Industry 4.0 wireless networks together with blockchain distributed ledger that ensures soundness, safety, and security through mining-based smart data technologies.	Chung *et al*., 2019; Din *et al*., 2019; Ferreras-Higuero *et al*., 2020; Hu *et al*., 2016; Ksentini *et al*., 2021

Table 4. Continued

Adequate approach of gathering, sharing, and processing thoroughgoing product manufacturing data in the course of machining processes is required for carrying out increased efficiency production.	Balica, 2022; Hawkins, 2022a; Zvarikova *et al.*, 2021
Internet of Things-based machine learning mechanisms can set up ubiquitous connections across wireless nodes, configuring a network that strengthens or stabilizes communications among algorithm-driven sensing devices without human interactions.	Dawson, 2022; Kovacova *et al.*, 2022a, b; Rice, 2022
Progresses in deep learning techniques enable image processing algorithms to improve themselves autonomously. Advancements in trained cognitive algorithms and deep learning techniques require developments in big data technologies.	Ferreras-Higuero *et al.*, 2020; Gordon, 2022; Sharma *et al.*, 2021;
Machine learning-based analytics, techniques, and algorithms are interpretive technologies that integrate groundbreaking cognitive capabilities within robots.	Beckett, 2022; Kovacova *et al.*, 2022a, b; Ksentini *et al.*, 2021
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Table 5. Synopsis of evidence regarding debated topics and descriptive results (research findings)

Cognitive manufacturing integrates artificial intelligence-based decision-making algorithms, real-time big data analytics, sustainable industrial value creation, and digitized mass production by leveraging shop floor data as regards design and maintenance, so as to advance, through automatically harnessing assets and equipments, cognitive processes by inspecting information from workflows and environment, consequently leading to resource use optimization.	Ding *et al.*, 2021; Dumitrache *et al.*, 2019; ElMaraghy & ElMaraghy, 2022; Emmer *et al.*, 2018
Cognitive technical systems can perceive situations and contexts, determine them, and choose either to use an operational strategy or configure a set of undertakings that tackle aspects of the identified circumstances, enabling the accomplishment of the established objectives.	Ding *et al.*, 2021; Dumitrache *et al.*, 2019; Peters, 2022a
A heterogeneity of measurement tools, approaches, and applications are employed in the manufacturing sector to set out a certain degree of product quality: a huge volume of devices and processes are deployed in quality management.	Emmer *et al.*, 2018; Mladineo *et al.*, 2022; Zvarikova *et al.*, 2021
Cognitive manufacturing systems promptly react to satisfy fluctuating demands and requirements in the shop floor, across the supply network, and as regards customer needs.	Casadei *et al.*, 2019; Hu *et al.*, 2019; Qin & Lu, 2021
Manufacturing systems should self-optimize production processes to attain adjustable, self-regulating, and error-tolerant fabrication throughout large-scale customization operations.	Hu *et al.*, 2019; Mladineo *et al.*, 2022; Qin & Lu, 2021;
Large-scale customization necessitates responsive and adjustable manufacturing processes for fabricating personalized products in varying batch proportions and large volumes inexpensively.	Casadei *et al.*, 2019; Ding *et al.*, 2021; ElMaraghy & ElMaraghy, 2022

Table 5. Continued

Industrial Internet of Things-enabled cognitive manufacturing can assist in processing huge volumes of real-time data across cyber-physical production systems.	Elia & Margherita, 2021; Li *et al*., 2021b; Liu *et al*., 2022
Deep-learning based cognitive technologies can optimize value creation capabilities of organizations that leverage advanced analytics and cyber-physical production systems, thus developing into cognitive enterprises in terms of technological infrastructure and organizational architecture, integrating smart data and computing processes so as to enhance situational awareness, resilience, agility, and reactivity.	Elia & Margherita, 2021; Li *et al*., 2021b; Liu *et al*., 2022
Technological upsides in cognitive digitalization can be attained through the integration of artificial intelligence-based decision-making algorithms, Internet of Things smart devices, industrial big data, and real-time process monitoring in sustainable product lifecycle management.	Cavallo *et al*., 2021; Chung & Yoo, 2020; Gain, 2021; Penumuru *et al*., 2020
Operational indicators facilitate networking among smart things through artificial intelligence-based decision-making algorithms, cyber-physical process monitoring systems, and real-time sensor networks in sustainable Industry 4.0.	Cavallo *et al*., 2021; Liu *et al*., 2022; Qin & Lu, 2021

Figure 1. PRISMA flow diagram describing the search results and screening

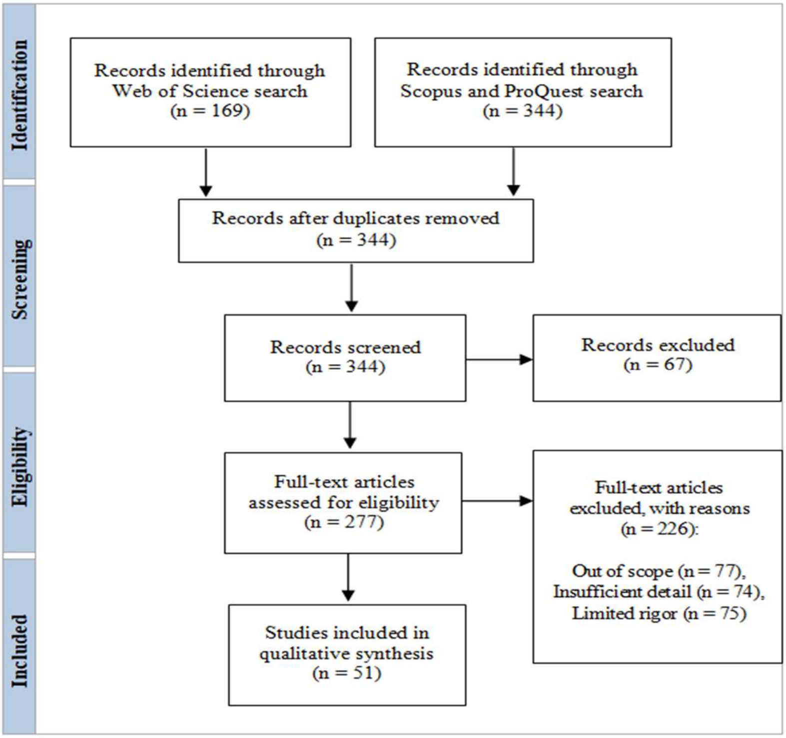

Figure 2. VOSviewer mapping of the topic regarding co-authorship

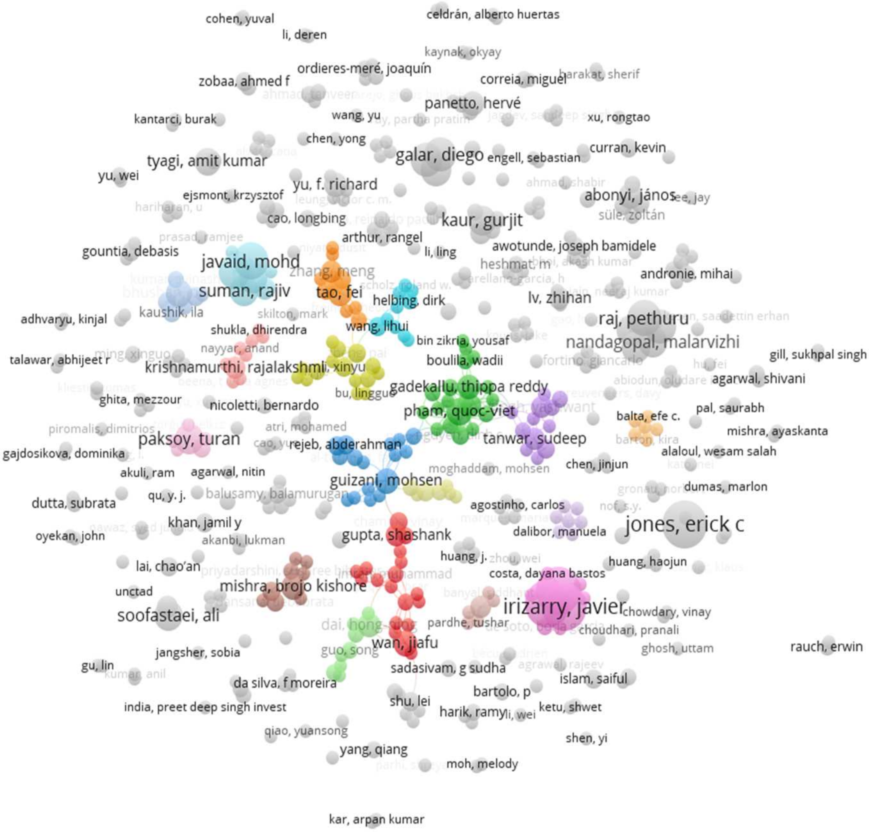

Figure 3. VOSviewer mapping of the topic regarding citation

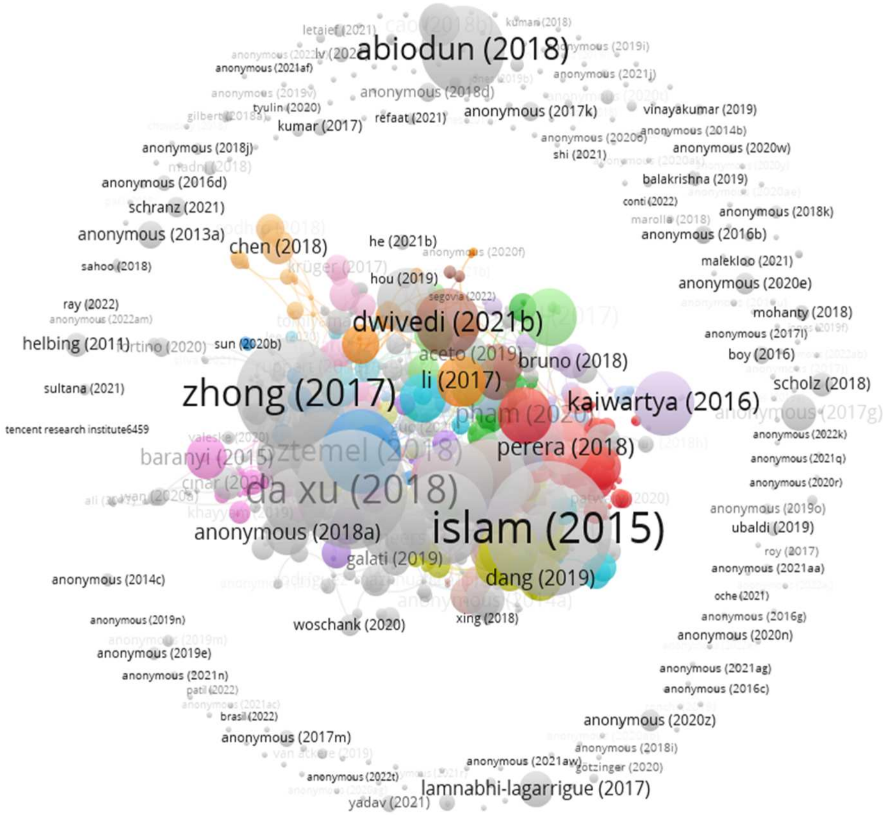

Figure 4. VOSviewer mapping of the topic regarding bibliographic coupling

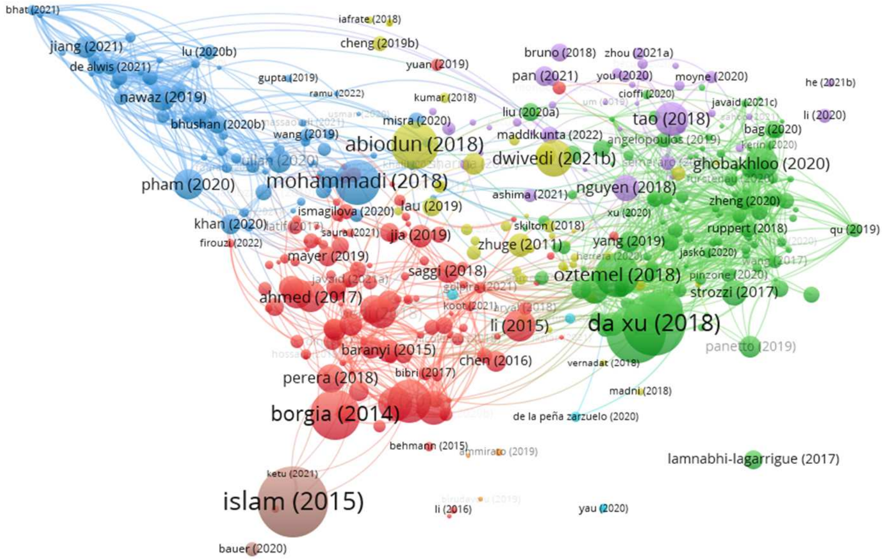

Figure 5. VOSviewer mapping of the topic regarding co-citation