Enhancing Autonomous Operations in Smart Objects and Devices through the Internet of Robotic Things

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Abstract – This study investigates the field of the Internet of Robotic Things (IoRT) and its capacity to transform the functioning of mobile context and robots' awareness systems. IoRT facilitates autonomous operations in smart objects and devices via the use of data analytics technologies, intelligent data processing tools, deep reinforcement learning, and edge computing techniques. This article examines the use of sensor networks, cloud robotics, machine learning algorithms, and collaborative context-aware robotic networks for the purpose of enhancing job performance, decision-making skills, and operational efficiency in diverse industrial and collaborative settings. The research also investigates the incorporation of route planning tools and motion, cognitive decision-making processes, and sensor data to improve the efficiency of robotic systems in tasks involving object handling. Furthermore, this study investigates the impact of cloud computing, wireless sensor networks, and cognitive approaches on enhancing inventory allocation procedures and company performance. The main purpose of this article is to provide a scholarly contribution to the field of IoRT by exploring its technological advancements and examining its potential applications across many sectors.

Keywords – Internet of Things, Internet of Underwater Things, Internet of Robotic Things, Internet of Drone Things, Internet of Clouds, Industrial Internet of Things.

I. INTRODUCTION

The Internet of Things (IoT) technology is establishing a robust foundation for customers to enhance the intelligence of their present equipment, enabling them to connect to the Web and facilitate the interchange of information across devices. The IoT is seeing significant growth, and the year 2018 is anticipated to be a captivating period for the IoT industry [1]. According to the most recent estimate published by Gartner [2], it is projected that by the year 2020, a total of 20 billion devices will be interconnected inside the IoT framework. Furthermore, the IoT industry is anticipated to generate a substantial revenue of $300 billion. The IoT has been identified as one of the five prominent themes in the year 2018 [3]. The concept is undergoing continuous development and resulting in notable advancements in innovation across various domains application. Consequently, new terminologies have emerged, like Internet of Nano Things (IoNT), Internet of Medical Things (IoMT), IoDT, Industrial Internet of Things (IIoT), Internet of Cloud Things (IoCT), Internet of Autonomous Things (IoAT), Internet of Mobile Things (IoMBT, and numerous others.

Robotic engineering systems are now used in several industrial sectors and are widely regarded as vital components for societal advancement within the context of the emerging digital era. The systems in industrial Internet of Robotic Things (IoRT) applications undergo transformation as technologies like AI, robotics, IIoT, intelligent networking, and electric mobility continue to advance. Recent advancements in intelligent connectivity have facilitated the seamless connection of robotic entities, allowing them to always establish links, in any location, and with other entities and individuals via diverse pathways, networks, and services. In prospective scenarios, a sophisticated network infrastructure that undergoes dynamic enhancements and expansions via the deployment of linked robotic entities, known as edge nodes, has the potential to function as the fundamental framework for applications of IoRT.

The concept of the IoRT encompasses the advancement of autonomous robotic models with the IoT and IIoT, as well as intelligent networking, cloud computing and distributed, Augmented/Virtual Reality (AR/VR), AI, Digital Twins (DT), swarm technologies, and Distributed Ledger Technologies (DLTs). These technologies allow intelligent objects to communicate and interact with one other in a distinct manner using the Internet. The expeditious advancement and implementation of multi-radio access technologies, facilitating the connectivity and interaction of devices and objects at the periphery of the IoRT, have resulted in the emergence of heterogeneous systems of mobile characterized by intricate configurations. Consequently, the management and maintenance of devices in these networks necessitate sophisticated approaches to effectively address the problems posed by future robotic entities.

The IIoT and IoT integration with robotics and AI is driving the rapid advancement of IoRT applications. This progress is enhancing the capabilities of contextually aware decision-making support systems, allowing the resolution of complicated operations, and facilitating the growth of machine intelligence. This phenomenon facilitates the integration of programming controls, and systems, as well as the usage of fundamental Internet technologies, to enhance the efficiency of implementing interactions with robotic entities. In accordance with conventional practices, robotics systems often have a programmable aspect that is specifically tailored for the purpose of carrying out repetitive tasks that are labor-intensive. These tasks encompass various functions such as detecting and responding to the surrounding environment. The advent of AI and ML has facilitated the operation of robotic entities via the use of learning algorithms and cognitive decision-making mechanisms, as opposed to conventional programming methods.

The integration of several fields and scientific disciplines (as seen in **Fig 1**) enables the improvement of autonomous programmable systems that include both machine learning and robotics. The interdisciplinary nature of the IoRT incorporates diverse perspectives from a wide range of academic fields. This facilitates the creation of solutions, which consider the reciprocal interactions and impacts among the various components of the IoRT.

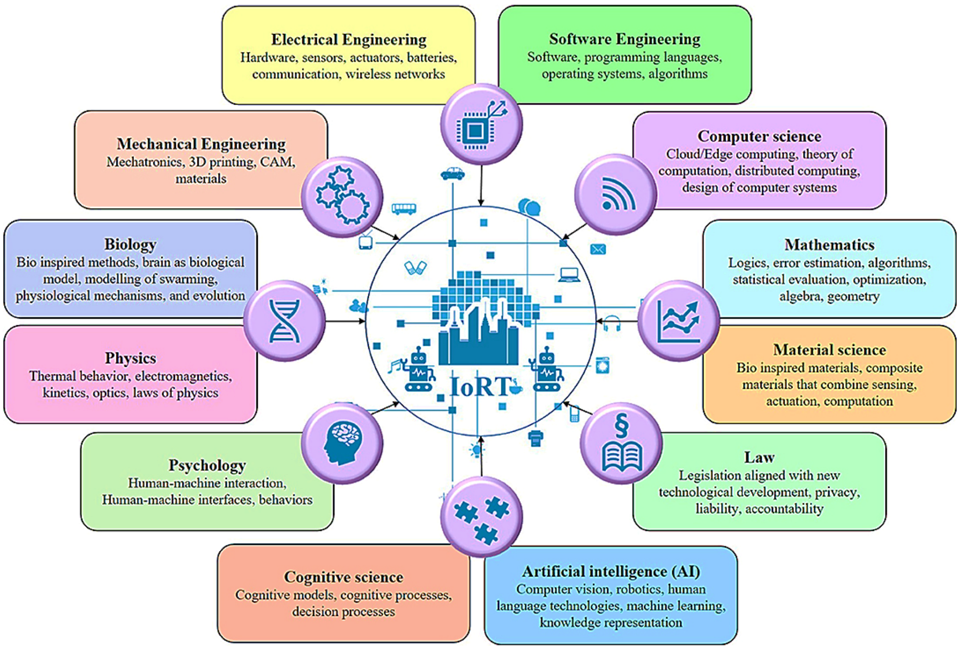


Fig 1. Fields and Scientific Disciplines of IoRT

The IoRT is an emerging field that holds the potential to revolutionize various industries by enabling autonomous capabilities in intelligent beings and devices. The main aim of this study is to examine various technologies and approaches that can enhance the performance, decision-making abilities, and operational effectiveness of IoRT systems. The objective of this study is to optimize the advancement of IoRT technologies and their integration across many sectors, such as smart manufacturing, industrial automation, and collaborative environments. This is accomplished through an analysis of the application of cloud robotics, sensor networks, and machine learning techniques.

The findings of this research carry substantial significance for scholars, practitioners, and organizations aiming to leverage the capabilities of the IoRT to optimize their operational efficiency and improve overall effectiveness. The rest of the article has been arranged as follows: Section II presents a literature review on the concept of IoT and robotics in smart objects. Section III defines the methodological aspect of the research. Section IV presents a discussion of the results obtained from the research. This section discusses big data and data analytics, remote big data management tools with IoRT, sensing and computing technologies in IoRT, and environmental mapping and visual perception algorithms within IoRT. Lastly, Section V draws a conclusion to the research.

II. LITERATURE REVIEW

According to the findings of Al-Fuqaha, Guizani, Mohammadi, Aledhari, and Ayyash [4], it has been observed that the communities associated with the IoT and robotics have traditionally pursued separate objectives, although these objectives have been found to be mutually advantageous. The primary objective of the IoT community is to provide information services that offer extensive sensing, tracking, and monitoring capabilities. In contrast, the robotics community has focused its efforts on the generation of action, the facilitation of interaction, and the attainment of autonomous behavior. As a result of this reasoning, there is an increasing claim that the incorporation of the IoRT, which combines insights from both factions, will yield substantial further advantages.

In the study conducted by Papazoglou and Van Den Heuvel [5], a service-oriented architecture was developed to enhance the operational efficiency of autonomous, mobile manufacturing units. These units have the ability to integrate data acquired from a peripheral sensing network for the purpose of identifying and analyzing disturbances. Hoffman [6] devised a distributed system that facilitates the exchange of data and coordination of collaborative activities between humans and robots. This system is coupled to a centralized task planner. Lines of production have also been conceptualized as multi-agent systems that include self-descriptive capabilities to minimize changeover and set-up durations. Furthermore, there have been advancements in the development of general-purpose middlewares that facilitate the coordination and control of dispersed tasks in IoRT settings.

The Ubiquitous Network Robot Platform86 (UNR-P86) [7] is a versatile middleware designed for IoRT settings, as seen in **Fig 2.** The system facilitates the transfer of operational control for services via the use of both physical and virtual robots. An illustrative example includes the reservation of a physical assistance robot by means of a virtual robot interface on a smartphone device.

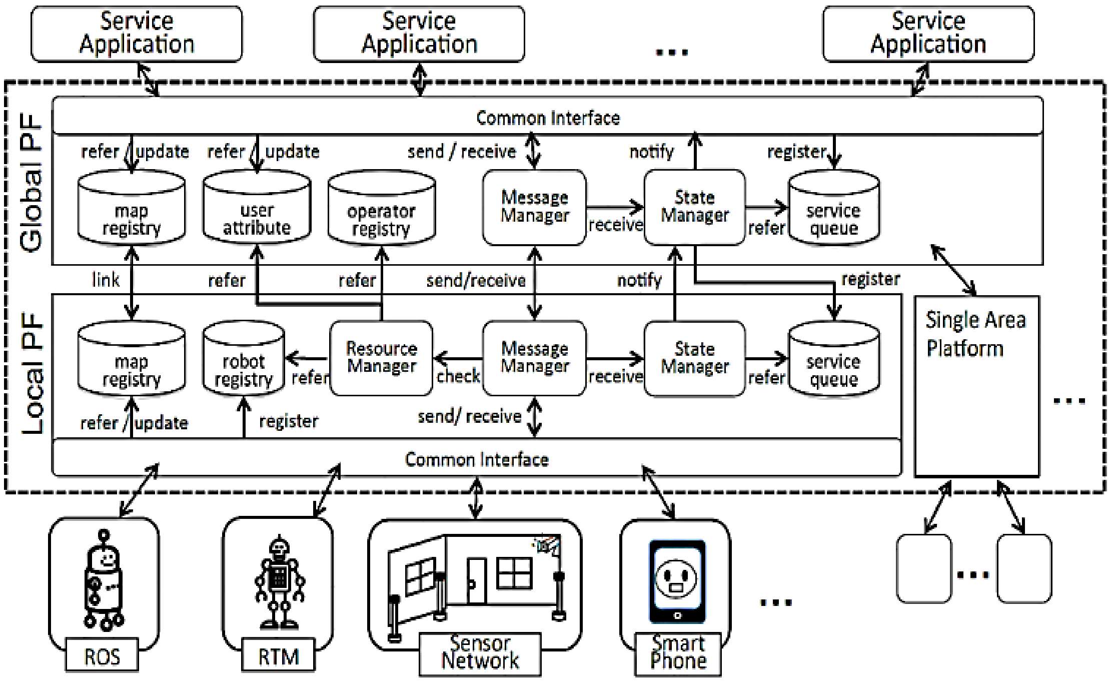


Fig 2. Ubiquitous Network Robot Platform with two layers

The Local Processing Facilities (LPFs) is responsible for configuring a robotic system inside a certain spatial domain. The General Purpose Framework (GPF) functions as an intermediary layer connecting the LPF of various regions with the service applications.

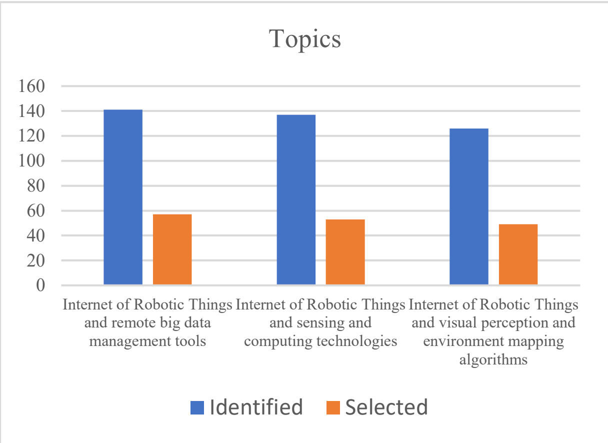
According to Benyoucef and Verrons [8], the integration of configurability with decision-making capacity may result in the capability of a system to autonomously configure itself. The process of self-configuration poses significant challenges inside an IoRT system, primarily due to the need for configuration algorithms to include both the modern interactions among the system's actors and their physical interactions within the actual world. The framework known as "PEIS Ecology" encompasses algorithms designed for the autonomous construction of a robot ecology. This framework enables the integration of various devices equipped with acting, sensing, and processing capabilities, like robots, to accomplish intricate functionality. The use of a shared tuple-space blackboard facilitates advanced levels of cooperation and enables the seamless adjustment of configurations in real-time.

The primary research inquiry addressed in this contribution is to the use of the IoRT for the purpose of establishing autonomous functionalities inside intelligent products and gadgets. This entails the use of data analytics, deep reinforcement learning, edge computing techniques, and intelligent data processing tools to facilitate autonomous activities and enhance operational efficiency across diverse sectors, including manufacturing. The study also places emphasis on the integration of sensor data, machine learning algorithms, and cloud computing technologies in order to augment the decision-making skills and situational awareness of autonomous systems operating in unfamiliar surroundings. Furthermore, the primary objective of this article is to enhance the connection networks of IoRT edge devices and enhance the performance of assets and operational efficiency by integrating sensor and actuator fusion, context awareness algorithms, and cloud data analytics.

III. METHODOLOGY

The use of a Shiny application was employed to implement the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) [9] criteria in order to construct a comprehensive diagram that incorporates evidence-based information that has been collected and processed, including the findings of the search and the processes for screening. A comprehensive review of the literature was done using the Web of Science, Scopus, and ProQuest databases between October and June 2022. The search terms employed were "IoRT " in conjunction with environment mapping algorithms" "remote big information tools of management," "visual perception, and "sensing and computing technologies." The examined study, which was published from 2016 to 2022, yielded a total of 404 sources that met the established eligibility criteria.

A comprehensive selection of 159 predominantly empirical sources has been carefully made, following the rejection of full-text studies that were considered irrelevant or lacked adequate rigour and sufficient information (**Fig 3** and **Table 1**). Intelligent workflows and AI, facilitated by the utilization of SRDR (Systematic Review Data Repository), AMSTAR, DistillerSR, and Dedoose, have been employed as tools for data extraction in the processes of literature collection, screening, and evaluation. These tools have also been utilized for document flow monitoring, as well as for the examination of qualitative and mixed methods research. Furthermore, they have been instrumental in establishing reliable outcomes and correlations. The process of bibliometric mapping via the use of data visualization was facilitated by using Dimensions AI. In terms of organizing the visual representation, the VOSviewer software was utilized.



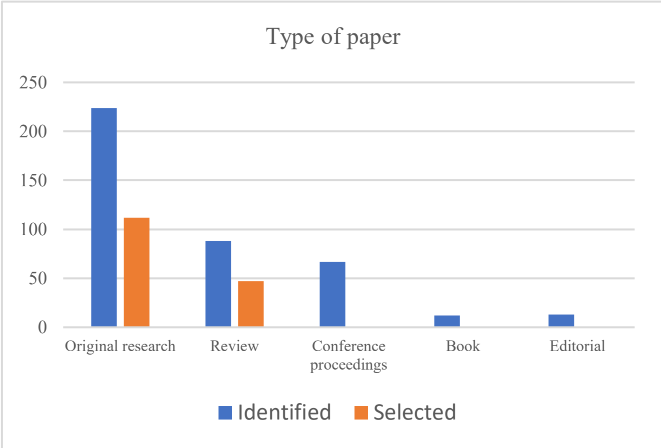


Fig 3. Identified and Selected Scientific Products, Classified as Topics and Types

Table 1. Cumulative Evidence Summary of The Pertaining to The Investigated Themes and The Descriptive Results Derived From the Study Findings

No.	Table 1: cumulative evidence Summary of the pertaining to the investigated themes and the descriptive results derived from the study findings	
1	IoRT is articulated in connection to smart devices and objects using intelligent tools of data processing and deep reinforcement learning, and edge computing methods. In collaborative industrial settings, sensor and robotic devices use IoT approaches and remote big data management tools spanning context-aware systems and data fusion.	Lee and Lee [10]
2	IoRT uses image capture devices, data processing algorithms, distributed intelligence tools, and computer vision to recognize, manipulate, and control objects. In intelligent Internet of Things settings, job scheduling and execution are configured by data processing algorithms, context-aware systems, and remote sensing.	Axelsson [11]
3	Autonomous collaborative multi-robot systems use robotic guiding technology, object identification algorithms and computer vision, image processing and data collecting tools, and adaptable industrial settings to accomplish tasks. Using smart sensing techniques, IoRT systems may be designed and modeled for object recognition, localization, mapping, and avoidance.	Noguchi, Will, Reid and Zhang [12]
4	Networked production management and real-time autonomous navigation are achieved by IoRT via the use of modeling and forecasting tools, industrial automation technology, and edge computing and visualization approaches.In cyber-physical manufacturing systems, interconnected goods and processes are developed using edge computing approaches, real-time predictive analytics, and ontological and semantic modeling tools across IoRT smart habitats.	Balaman, Wright, Scott, and matopolous [13]

IV. RESULTS AND DISCUSSION

Big data and data analytics

The growing demand for accessing informational resources in contemporary digitalized societies has amounted to the extensive utilization of the term "big data" by corporate organizations, IT professionals, and scholars. The idea of big data, as discussed by Wu, Zhang, Shen, Mo, and Peng [14], incorporates various elements including computer trends, information processing, computational methods, analytical tools, and the influence of socio-cultural developments on both business and society. Nevertheless, it is imperative to acknowledge that a globally recognized and standardized formal definition of big data is currently lacking. The absence of a unanimous agreement suggests that the phrase 'big data' can encompass diverse definitions, interpretations, and implications for different entities, as inferred by Floridi [15]. The concept of "big data" has been defined by four important features, including truthfulness, volume, diversity, and velocity, as stated by previous research conducted by Gandomi and Haider [16]. Nevertheless, other researchers, including Opresnik and Taisch [17]; Günther, Mehrizi, Huysman, and Feldberg [18], and Côrte-Real, Oliveira, and Ruivo [19], have put forth the suggestion of incorporating an extra dimension, referred to as "value." This pertains to the advantages and utility that users obtain from employing the examined data to inform their decision-making processes.

In relation to 'big data', Wu, Zhu, Wu, and Ding [20] have discerned four primary 'prevalent notions' or 'themes' that include the core elements of big data. These themes, including data, technology, techniques, and effect, are considered vital components within the realm of big data research. In addition, Vogel et al. [21] put forth a formal definition of big data that takes into account the current definitions and primary research areas. According to their proposal, big data refers to information assets that possess an important variety, velocity, and volume, necessitating the use of specialized technology and analytical methods to extract value from it. The provided definition of big data pertains explicitly to the use of specialized technologies and methodologies for the purpose of analyzing the gathered information. In their study, Wu, Liao, Tseng, Lim, Hu, and Tan [22] contend that the unique attributes of big data, such as its substantial magnitude, diverse structural composition, rapid generation rate, imprecise and uncertain nature, fluctuating data flow rates, and low value density, necessitate the utilization of data analytic techniques by organizations. These techniques enable the analysis and extraction of useful insights from big data, thereby facilitating the acquisition of intelligence.

Furthermore, according to [23], technology serves as the fundamental infrastructure for business intelligence systems, allowing organizations to obtain precise and valuable information through the utilization of big data analytics. This enables a comprehensive understanding of market positions, optimization of strategic decision-making processes, and the monitoring of organizational competitiveness. According to Mohanty, Jagadeesh, and Srivatsa [24], the ongoing discussion is on the methods by which organizations may effectively extract value from big data, considering the highly competitive nature of the market and the abundance of extensive, diverse, and intricate datasets available for analysis. According to [25], the application of digital technologies results in the generation of vast quantities of data. These data must be effectively kept and analyzed in order to extract their inherent value, which in turn enables the implementation of data analytics in the process of decision-making within organizations. For instance, by utilizing big data, retail enterprises have the potential to gather valuable insights regarding store footfall, customer demographics such as age and gender, and their behavioral patterns within the store. These insights can be effectively utilized to inform decision-making processes related to product promotion strategies, staff selection and placement, and other relevant considerations.

Therefore, organizations are compelled by situational demands to use technology capabilities in order to make quick, accurate, and effective operational and strategic decisions using of big data management strategies. Furthermore, the ongoing progress and evolution of technology will result in an increasing flow of digitized data. This will necessitate the integration of individuals, processes, and organizations in order to effectively utilize this data for innovation, knowledge management, gaining a competitive advantage, and adding value to businesses. Huberty [26] assert that organizations have the potential to derive value from big data at individual level by using data interconnection and portability. Additionally, they argue that value may be realized via interactions at different levels, achieved by aligning work practices, organizational-business models, and stakeholders' interests. Key findings of this topic in the context of smart industries is portrayed in **Table 2**.

No.	Table 2. Summary of Major Findings in This Topic	
1	In light of fierce competition in the marketplace and the accessibility of vast, diverse, and intricate information, discussions over how businesses might get value from big data at varying degrees of analysis persist.	Mandel [27]
2	Big data is produced by digital technologies, which must be analyzed and stored in order to extract value and enable the incorporation of data analytics into the organization's decision-making processes.	Kamilaris, Kartakouillis and Prenafeta-Bold [28]
3	Retail businesses could use big data to gather intelligence on customer traffic, age and gender distribution, and in-store movement patterns. This information could then be used to inform decisions about staff placement and selection, product promotion policies, and other matters.	Akter and Wambo [29]

Remote big data management instruments in the IoRT

The integration of data analytics technologies, edge computing, and deep reinforcement learning techniques facilitates the implementation of the IoRT. This integration enables the seamless interaction between smart devices and objects, allowing for autonomous operations. Cloud robotics is a field that involves the use of real-time sensor data, including the application of natural language tools of processing and DNN (deep neural networks). These technologies are employed for various purposes such as perception, monitoring, and making of decision in relation to object tracking, identification, and recognition. Cyber-physical systems, sensor technologies, and autonomous robots have the potential to be used in smart manufacturing operations via the integration of actual-time information and the automation of entrepreneurship processes. Cloud robotics focuses on the advancement of language processing algorithms and systems, with the objective of gathering operational data in real-time. Smart gadgets, context-aware systems, and artificial neural networks enhance the capability of continuously detecting and monitoring contextual data inside the surrounding environment. In collaborative industrial environments, the use of IoT methods is facilitated by robotic and sensor devices. These devices make use of context-aware systems and data fusion. Multi sensor fusion and wireless network technologies play a crucial role in facilitating remote intelligent objects and processes identification by using image detection and recognition techniques.

The integration of data fusion and cloud computing technologies, together with the use of algorithms of deep learning and CNN, facilitates the implementation of image and voice recognition procedures. Sensor equipment is supported in its cognitive decision-making processes by the use of data mining, fusion, and processing techniques. Virtual machines and mobile robotic devices are supported in their computation-intensive activities by technologies such as image and speech recognition, mobile cloud computing tools, natural language processing, and situational awareness algorithms. The field of IoRT utilizes data processing methods and computer vision, together with distributed intelligence tools and image collecting devices, to facilitate object control, manipulation, and detection. The use of mobile robot techniques and machine intelligence enhances the precision of picture recognition, hence enabling the efficient execution of cloud-based production processes and activities. Mobile and wireless technologies play a crucial role in enhancing operational efficiency by supporting autonomous swarm robots in cloud and smart manufacturing processes, as well as facilitating remote administration of large data. Wireless data transfer is a crucial component of industrial automation and cloud-based operational technologies, as it facilitates the seamless integration of predictive maintenance tools and smart manufacturing processes into production facilities.

Robotic technologies are capable of doing activities that are driven by data through the usage of edge and fog computing techniques. The use of visualization tools and data mining, coupled with algorithms of object identification, together with the incorporation of fog and edge computing technologies, serves to enhance the operational efficiency of intelligent sensors and devices. Spatial information processing and collecting technologies enhance the interoperability of the IoRT and virtual machines via the use of interconnected sensors and devices. The capabilities of making decisions of networked and cloud robotics involve the integration of geospatial-temporal information by leveraging remote big information systems of management. Cloud computing provide support for virtual machines and IoRT systems in terms of scalability and connection. Collaborative and autonomous robots enhance manufacturing processes and production workflows via the use of digital twins and data collecting systems within smart factory environments.

The development of cognitive and cloud robotics in I4.0 involves the integration of actuators and sensors into cyber-physical systems deployed in facilities of manufacturing. Deep learning and machine learning approaches perform a role in the field of picture classification and object identification via the use of synthetic data generation. Heterogeneous networked IoRT devices need the integration of mobile actuators and sensors. Robotic operating systems effectively execute activities via the use of intelligent networked devices and remote management tools for handling large volumes of data.IoRT devices use machine learning algorithms, interconnected sensors, wireless technologies, and cloud computing to facilitate the real-time gathering of data pertaining to device diagnostics and management. Sensor networks play a crucial role in facilitating the IoRT objects by using remote big data management solutions.

The exchange of sensor data enhances the monitoring skills of robots in terms of obstacle manipulation and avoidance activities. Networked robotic systems and IoRT devices engage in the interchange of sensor data to accommodate dispersed compute resources, adapt to changing environments, and adjust to varying operating circumstances. Mobile autonomous robots are capable of controlling and monitoring linked items and sensor networks by using cloud computing technology. Virtual machines and cloud-networked robots are built upon the foundations of context-aware systems, location identification technologies, big data analytics, and image processing. Collaborative context-aware robotic networks facilitate the dissemination of environmental data across processing units in the IoRT. The use of vision sensing technology, coupled with the implementation of route planning and job scheduling algorithms, as well as the incorporation of collision-free instruments, has been seen in many academic studies and research endeavors.

This paper aims to examine the concept of cloud robotics within the context of industrial automation, specifically focusing on the autonomous job allocation and operational choices involved. The motion detecting capabilities of mobile robots effectively coordinate activities via the use of route planning algorithms (refer to **Table 3**).

No.	Table 3. Summary of the key Findings in This Topic	
1	The integration of deep reinforcement learning tools and intelligent data processing, together with data analytics technologies and edge computing techniques, facilitates the implementation of the IoRT in the context of smart objects and gadgets. The integration of robotic and sensor devices in collaborative industrial settings is simplified through the utilization of IoT approaches and remote big information management systems. This facilitates the integration of data and the deployment of context-aware solutions.	Zhou, Xu, Li, Zeng, Luo, and Zhang [30]
2	The concept of IoRT utilizes computer vision and data processing methods, together with picture distributed intelligence tools and collecting devices, to facilitate object control, detection, and manipulation. In smart IoRT settings, the configuration of job scheduling and execution is facilitated using data processing algorithms, context-aware systems, and remote sensing technologies.	Vasile, Pop, Tutueanu, Cristea, and Kolodzieji [31]
3	Collaborative autonomous multi-robot systems are used in adaptable industrial situations via the utilization of robotic guiding technologies, data collecting tools and image processing, object identification, and robotic guiding technologies. The modeling and design of IoRT systems include the use of intelligent sensing technologies to provide object identification, localization, mapping, and avoidance capabilities.	Hu, Niu, Carrasco, Lennox, and Arvin [32]

Computing and sensing technologies in IoRT

Mobile context awareness systems and autonomous robots use CNN, machine learning techniques, and sensor devices for the purpose of auditory environment detection. The use of imaging-based navigation technologies and immersive visualization enhances situational awareness and facilitates efficient, thorough, and systems of mobile robotic operational behavior in unfamiliar habitats and intuitive decision-making. The use of sensor data and route planning algorithms has been shown to enhance productivity in augmented and virtual operational habitats, particularly in unstructured circumstances. Deep learning algorithms are used in sound recognition systems, and visual recognition technologies to enable mobile devices to understand and respond to their surrounding environment. These technologies employ mechanisms for data processing and fusion, allowing for context awareness in mobile contexts. The use of decision support and multi-agent systems, as well as remote sensing and machine learning techniques, facilitates the ability of robotic networks to make independent judgments. Connected collaborative robots and IoRT mobile devices are capable of gathering and sensing data from their surrounding environment. This data is sent over cloud computing and fog networks, using their compute and storage capacities.

Robotic operating systems has the ability to autonomously execute activities by using their situational and contextual awareness skills, particularly in the context of collaborative and interactive work inside smart habitats. Robotic devices make use of machine perception and distributed sensing technologies, as well as deep learning and ambient intelligence methods. These devices integrate route planning tools, sensor data, motion, sensing and perceptual capabilities, and cognitive decision-making processes. The enhancement of robotic system performance for object manipulation tasks is facilitated by several components, including computer vision systems, obstacle detection and trajectory planning tools, motion control algorithms, and machine learning algorithms. The optimization of robotic agent behaviors in uncontrolled settings is facilitated using computing technologies and edge surveillance, visual modelling, and image processing, as well as DNN. Collaborative and cognitive robotics include the use of multi-sensor data fusion technologies, tools for object mapping, localization, and identification, as well as autonomous navigation systems. Mobile robot motions may be characterized using route planning techniques, obstacle avoidance, and sensing technologies, as well as object recognition algorithms and machine learning for tracking and detection purposes [40].

Decision support agents use computer vision and image enhancement technologies, as well as geolocation data intelligence, to facilitate intelligent decision-making processes. Predictive geospatial modeling tools play a crucial role in facilitating autonomous object identification, recognition, and categorization via the use of computer technology and sensing. Motion planning algorithms, scheduling algorithms, and simulation and modeling tools have been used to improve robotic and cyber-physical and systems. These tools and algorithms aid in completing and managing job allocation and configuration. The management of IoRT devices plays a significant role in shaping many domains such as cloud computing, collaborative robotics, and cognitive robotics. This is achieved via the use of context awareness algorithms and predictive modeling techniques.

Autonomous robots are enhanced by the integration of processing capabilities, data processing tools and predictive maintenance, as well as sensor devices and data. This integration serves to optimize machine performance. Deep neural networks, blockchain technologies, computational intelligence tools, machine learning algorithms, smart habitat modeling, and deep learning algorithms play a crucial role in the autonomous identification of visual objects by means of decentralized governance, transmission, and data collection. The utilisation of signal processing and data capture technologies is of utmost importance in improving the precision of localization in autonomous robotic systems, particularly when dealing with different sound sources in simulated environments and sensor networks that are spread out. The utilization of blockchain technology and autonomous systems has had a positive impact on enhancing the interconnection and networking capabilities of IoRT devices. The objective is accomplished by the utilization of machine learning algorithms, collaborative methodologies, decision-making procedures, and decentralized data sharing.

The achievement of object manipulation and identification may be facilitated by using mapping sensors and robotic habitat recognition inside intelligent virtual habitats. Machine learning and computer vision algorithms, together with ambient intelligence and image recognition technologies, as well as smart sensor devices, have the capability to configure trajectory pathways and identify events via the constant monitoring of processes and gathering of data. The cooperative and synchronized operation of robotic networks is influenced by the seamless mobility and interoperability of data and sensors. Autonomous robots are designed to operate independently by using computer vision capabilities, convolutional neural networks, object tracking algorithms, and deep learning techniques.

These technologies are used to facilitate navigation jobs inside smart systems of the habitat. IoRT systems and cloud networked robotics use deep learning algorithms and autonomous learning capabilities to enhance object tracking, motion, mapping, and detection functionalities. The integration of sematic technologies, wireless sensor networks, navigation and location tools is seen in the realm of the IoRT. The use of heterogeneous embedded devices, sensing equipment, and real-time operating robotic systems facilitates efficient and rapid transmission of data. The development of IoT-based robots is facilitated using real-time computer processing tools, automation systems, and cloud computing. The understanding of the spatial surrounds and ambient environment in robotics heavily relies on sematic technologies, computer vision algorithms and actuation and sensing capabilities. Cognitive and cloud robotics are influenced by the integration of 3D assembly, sematic data, actuators, and sensors.

Big data analytics, cloud imaging tools, machine learning algorithms, and distributed intelligence have been shown to significantly improve the operational efficiency of firm robots in both collaborative workplaces and manufacturing firms. This is achieved via the use of location monitoring and tracking mechanisms. Cloud-connected devices are capable of gathering and examining data, overseeing, and supervising manufacturing processes and the connectivity of industrial assets, and enhancing the efficiency of product development activities (refer to **Table 4**).

No.	**Table 4. Summary of the Key Findings in This Topic**	
1	Mobile context awareness systems and autonomous robots use convolutional neural networks, machine learning techniques, and sensor devices for the purpose of auditory environment detection. In the realm of the collaborative robots, mobile devices, and IoRT are interconnected to collect and perceive data from their immediate surroundings. This data acquisition process occurs via the use of cloud computing and fog networks.	Morocho-cayamcela, Lim, and Lee [33]
2	Blockchain technology and autonomous systems contribute to the improvement of device connectivity and networking in the IoRT via the implementation of machine learning algorithms, decision-making processes and decentralized data sharing, and collaborative methodologies. IoRT systems and cloud-networked robotics use deep learning approaches and autonomous learning capabilities to enhance item motion, identification, mapping, and tracking.	Bahramirad, Paaso, and Yan [34]
3	The concept of IoRT involves the use of visualization and edge computing methods, firm automation technologies, forecasting and simulation tools. These components are employed to achieve networked production management and real-time autonomous navigation by means of distributed computing systems. The development of interconnected processes and goods in cyber-physical manufacturing systems is facilitated by the use of ontological modeling and semantic tools, edge computing approaches, and real-time predictive analytics inside IoRT smart habitats.	Cao, Liu, Meng, and Sun [35]

Environment mapping and visual perception algorithms in the IoRT

In IoRT settings, the enhancement of inventory allocation procedures and business performance is achieved via the use of cyber-physical and autonomous robotic systems. These systems include dynamic and computational reconfiguration capabilities, semantic technologies, and data analytics, as well as distributed intelligence tools. When setting up IoRT systems and cloud robotics, edge computing technologies such as sensor networks, situation awareness algorithms and smart connected items are brought together. These components are employed for decentralized task scheduling, which is enabled by environment mapping and visual perception algorithms. Robot swarms have their decision-making capacities improved by use of IoRT sensors and intelligent data manipulation tools that facilitate watching, following and influencing things. Cognitive approaches, wireless sensor networks, and cloud computing technology play a crucial role in supporting IoRT systems and intelligent items.

Virtual, cognitive, and mobile robots effectively amalgamate sensor data. IoRT (Internet of Robotic Things) systems are capable of executing tasks involving several machines and facilitating coordinated and collaborative operations. This is achieved via the use of route planning algorithms, movement trajectory tools and real-time multifunction monitoring, and convolutional neural networks. IoRT systems has the capability to make informed judgments via the use of acquired image data and object identification algorithms. These systems also employ multi-machine cooperation and collaborative operation mechanisms to effectively accomplish given tasks in a flexible manner. IoRT systems execute their designated duties by using trajectory tracking tools, obstacle avoidance algorithms, and versatile habitat monitoring systems, which are interconnected with performance assessment, mobile control, movement process, and coordinated operation. Actuator and sensor fusion, context awareness algorithms, and device control technologies have been shown to enhance the networks of connection of IoRT.

The use of event sensing, together with cloud data analytics and edge computing technologies, has been shown to enhance the performance of assets and increase operational effectiveness. The integration of interoperable controlling mechanisms, various edge data processing tools, and smart actuators and sensors is a key feature of IoRT cloud analytics. The connection of IoRT devices is influenced by several technologies like as fog and cloud computing, visualization tools, event processing tools, and machine learning algorithms. These technologies play a significant role in facilitating device connectivity by using environmental mapping and visual perception methods.

Navigation management tools, linked virtual devices, and spatial mapping techniques are used to configure swarm robots and networked IoRT cloud in the context of smart industrial maintenance. Mapping and environment sensing tools, collision avoidance algorithms, as well as cloud computing technologies, play a crucial role in facilitating job coordination and enhancing performance in multi-robot systems. The use of cloud-based object tracking and data mining techniques significantly amplifies the computational capacities of virtual machines and mobile robots, enabling them to function autonomously as agents. The identification and perception of objects are of utmost importance in the navigation of robots, namely in terms of facilitating coordination and collaboration to guarantee the avoidance of collisions and the establishment of virtual paths. The coordination of actions in swarm and cloud robotics is impacted by the utilization of local sensing and decentralized communication methods. These methods entail the monitoring of the trajectory of IoRT devices. Smart machines and mobile swarm robots possess the ability to exchange control signals and collected data, hence facilitating coordinated decision-making and collision avoidance through the utilization of wireless communication technology. This enables individuals to effectively execute complex independent tasks.

In collaborative multi-robot environments, the effective deployment of communication network technology is very important since it is a crucial way of tracking the trajectories and avoiding collisions. Robotic communication systems are able to collect data in a sophisticated way from their immediate environment. These systems work on their own through wireless sensor networks as well as employing algorithms for mapping the environment and visual perception. Deep learning, machine learning, and artificial neural networks are used to optimize the efficiency of collaborative robot communication in relation to autonomous operations. To enhance control systems and path tracking of robots using crowd navigation techniques, deep reinforcement learning is employed. In order to ensure that numerous mobile and autonomous swarm robots function effectively, there has to be a high degree of accuracy in forecasting obstacles, planning routes, mapping and avoiding hindrances involved. This requires real-time data collection and processing methods. The utilization of machine learning techniques and cloud computing technologies is evident in the application of multi-robot systems and IoRT devices.

The utilization of IoT technology within robotic systems and interconnected gadgets facilitates the implementation of cooperative endeavors. The aforementioned objective is accomplished by the utilization of remote sensing environmental data for collision mitigation and task allocation, facilitated by motion capture systems in heterogeneous and non-linear situations. Mobile autonomous and cloud networked robots has the ability to combine sensory and computation skills in order to carry out coordinated actions inside dynamic situations. Data visualization and analysis tools, as well as route planning and data fusion algorithms, play a crucial role in supporting robot sensor networks and robotic technologies in their ability to recognize and track objects. Additionally, machine intelligence further enhances these capabilities. IoRT systems use environmental monitoring mechanisms to collect sensor data and employ environment mapping and visual perception algorithms to integrate networked operations. The development of robotic monitoring capabilities in industrial environments is facilitated by several factors, including sensor technologies, machine data and production operation, simulation, and modeling tools.

The use of process planning and sensing technologies plays a crucial role in configuring AI-based machine prognosis and performance. This, in turn, has a significant impact on the overall performance of production systems and the modeling of these systems via the application of real-time data analytics. Cognitive AI facilitates the diagnosis and monitoring of line management production in dynamic firm habitats, leading to significant improvements in efficiency. Technology of computer vision is of utmost importance in improving awareness and monitoring the factor of equipment. It also aids in supporting real-time production scheduling within the management of smart manufacturing framework. Algorithms of deep and machine learning have the capability to efficiently analyze large quantities of industrial data inside visual simulation environments, particularly in relation to the identification and diagnosis of faults. The achievement of smart manufacturing process monitoring, and control may be facilitated by the implementation of distributed intelligence, which involves the analysis of performance data and the optimization of production processes. Artificial intelligence (AI)-based analytical tools have the capability to use sensor data for the purpose of diagnosing faults in manufacturing facilities.

Coordination mechanisms and robotic cooperative behaviors have been shown to effectively achieve tasks by using coordinated motion planning and collision-free techniques. Autonomous robotic systems have the capability to effectively manage coordinated and unexpected activities via the use of machine learning methodologies, swarm intelligence algorithms, simulation, and modeling tools. The effective functioning of decentralized task execution, assignment, and allocation relies heavily on the integration of collective, coordinated, and cooperative behavior among robotic entities. This entails the use of object localization, mapping, and manipulation techniques. In the realm of multi-robot control systems, the primary function is to see and feel the surrounding environment to effectively carry out tasks. This entails the ability to make synchronized assessments, manipulate objects, and execute procedures for avoiding collisions.

The achievement of optimizing trajectory planning and ensuring collision-free mobility in dynamic unknown environments is facilitated through the utilization of robotic coordination systems and cooperative activities. Deep reinforcement learning algorithms are commonly employed for the purpose of controlling many robots in different activities, integrating but not limited to motion planning and object manipulation. These strategies facilitate the implementation of cooperative control among several actors. The utilization of performance modeling and fusion technology of multi-sensor in the context of route planning, and task fulfillment facilitates the execution of autonomous robotic behavior algorithms (**Table 5**).

No.	**Table 5. Summary of the Key Findings in This Topic**	
1	Autonomous robotic and cyber-physical systems employ semantic advancements, data analytics, and distributed intelligence tools to facilitate dynamic and computational reconfiguration capabilities. IoRT systems enable the efficient execution of intricate operations that include multiple robots through the utilization of route planning algorithms, trajectory, and real-time monitoring tools, as well as convolutional neural networks. These technologies facilitate synchronized and cooperative maneuvers, hence augmenting the efficacy and proficiency of robotic operations.	Leitao, Colombo, and Karnouskos [36]; Kıranyaz, Avcı, Abdeljaber, İnce, Gabbouj, and Inman [37]
2	The combination of local sensing and decentralized communication significantly impacts the coordination of actions in swarm and cloud robotics, as it facilitates the tracking of trajectories of IoRT devices. Autonomous robotic systems employ simulation and modeling technologies, cognitive decision algorithms, as well as visual navigation and route planning tools to augment the efficacy of remote sensing.	Smith [38]
3	IoRT devices use data sensor fusion and cloud computing technologies to enhance their capabilities in perceiving and detecting objects and environments inside dynamic operating systems. The dynamic and complicated behavior of IoRT devices is influenced by several factors such as cloud and edge intelligence, actuation and sensing technologies, and data sharing capabilities.	Munir, Blasch, Kwon, Kong, and Aved [39]

V. CONCLUSIONS

Extensive research has provided a comprehensive understanding of the role of actuator and sensor devices in facilitating autonomous mobility for multi-robot systems. Moreover, these devices contribute to the optimization of job allocation, administration, and execution by using data streams from the IoRT. The achievement of object identification and manipulation may be realized by using robotic environment recognition and mapping sensors, hence enhancing the efficiency of product development processes. Cloud-connected devices are used to collect and evaluate data, as well as to monitor and track production processes and the connectivity of industrial assets. Wireless data transfer is a crucial component in the implementation of industrial automation and cloud-based operational systems inside production facilities operating in smart virtual habitats. The use of sensor data, semantic interoperability, and machine learning algorithms are vital in boosting the effectiveness of multi-robot planning strategies, by seamlessly combining predictive maintenance tools and smart manufacturing techniques. Navigation and localization systems in smart robotic environments use actuating and sensing device capabilities to map the surrounding environment and execute various tasks.

This systematic literature review aims to examine pertinent peer-reviewed sources that explore the need of mobile actuators and sensors for monitoring robotic processes and systems in the context of heterogeneous linked modeling technologies, cognitive computing, and IoRT devices. The precision of sensors plays a crucial role in the performance and dependability of IoT-enabled robotic swarms, as it is facilitated using remote big data management systems. The use of event sensing and actuating tools, together with cloud data analytics, and edge computing technologies, has been shown to enhance the performance of assets and increase operational effectiveness. Robotic systems have the potential to enhance productivity in situations characterized by unknown circumstances and controlled parameters. Additionally, they may contribute to the improvement of performance and competitiveness of IoRT smart goods, particularly in synthetic simulation environments. Robotic devices use a combination of deep learning methods, ambient intelligence, machine perception and distributed sensing technologies. These technologies enable the integration of sensing and perceptual capabilities, cognitive decision-making processes, and sensor data, as well as route and motion planning tools.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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References
[1]. A. Khanna and S. Kaur, "Internet of Things (IoT), Applications and Challenges: A Comprehensive review," Wireless Personal Communications, vol. 114, no. 2, pp. 1687–1762, May 2020, doi: 10.1007/s11277-020-07446-4.
[2]. "Gartner forecasts worldwide IT spending to grow 8% in 2024," Gartner, Oct. 18, 2023. https://www.gartner.com/en/newsroom/press-releases/2023-10-18-gartner-forecasts-worldwide-it-spending-to-grow-8-percent-in-2024
[3]. E. E. Cranmer, M. Papalexi, M. C. T. Dieck, and D. Bamford, "Internet of Things: Aspiration, implementation and contribution," Journal of Business Research, vol. 139, pp. 69–80, Feb. 2022, doi: 10.1016/j.jbusres.2021.09.025.
[4]. A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of Things: A survey on enabling technologies, protocols, and applications," IEEE Communications Surveys and Tutorials, vol. 17, no. 4, pp. 2347–2376, Jan. 2015, doi: 10.1109/comst.2015.2444095.
[5]. M. P. Papazoglou and W. -j. Van Den Heuvel, "Service oriented architectures: approaches, technologies and research issues," The VLDB Journal, vol. 16, no. 3, pp. 389–415, Mar. 2007, doi: 10.1007/s00778-007-0044-3.
[6]. G. Hoffman, "Evaluating fluency in Human–Robot collaboration," IEEE Transactions on Human-Machine Systems, vol. 49, no. 3, pp. 209–218, Jun. 2019, doi: 10.1109/thms.2019.2904558.
[7]. A. H, A. Ramu, and S. Murugan, "Cognitive Radio Communication and Applications for Urban Spaces," Computing and Communication Systems in Urban Development, pp. 161–183, 2019, doi: 10.1007/978-3-030-26013-2_8.
[8]. M. Benyoucef and M.-H. Verrons, "Configurable e-negotiation systems for large scale and transparent decision making," Group Decision and Negotiation, vol. 17, no. 3, pp. 211–224, Apr. 2007, doi: 10.1007/s10726-007-9073-y.
[9]. D. Moher et al., "Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement," Systematic Reviews, vol. 4, no. 1, Jan. 2015, doi: 10.1186/2046-4053-4-1.
[10]. I. Lee and K. Lee, "The Internet of Things (IoT): Applications, investments, and challenges for enterprises," Business Horizons, vol. 58, no. 4, pp. 431–440, Jul. 2015, doi: 10.1016/j.bushor.2015.03.008.
[11]. P. Axelsson, "Processing of laser scanner data—algorithms and applications," Isprs Journal of Photogrammetry and Remote Sensing, vol. 54, no. 2–3, pp. 138–147, Jul. 1999, doi: 10.1016/s0924-2716(99)00008-8.
[12]. N. Noguchi, J. D. Will, J. F. Reid, and Q. Zhang, "Development of a master–slave robot system for farm operations," Computers and Electronics in Agriculture, vol. 44, no. 1, pp. 1–19, Jul. 2004, doi: 10.1016/j.compag.2004.01.006.
[13]. Ş. Y. Balaman, D. G. Wright, J. A. Scott, and A. Matopoulos, "Network design and technology management for waste to energy production: An integrated optimization framework under the principles of circular economy," Energy, vol. 143, pp. 911–933, Jan. 2018, doi: 10.1016/j.energy.2017.11.058.
[14]. Y. Wu, W. Zhang, J. Shen, Z. Mo, and Y. Peng, "Smart city with Chinese characteristics against the background of big data: Idea, action and risk," Journal of Cleaner Production, vol. 173, pp. 60–66, Feb. 2018, doi: 10.1016/j.jclepro.2017.01.047.
[15]. L. Floridi, "Big data and their epistemological challenge," Philosophy & Technology, vol. 25, no. 4, pp. 435–437, Nov. 2012, doi: 10.1007/s13347-012-0093-4.
[16]. A. H. Gandomi and M. Haider, "Beyond the hype: Big data concepts, methods, and analytics," International Journal of Information Management, vol. 35, no. 2, pp. 137–144, Apr. 2015, doi: 10.1016/j.ijinfomgt.2014.10.007.
[17]. D. Opresnik and M. Taisch, "The value of Big Data in servitization," International Journal of Production Economics, vol. 165, pp. 174–184, Jul. 2015, doi: 10.1016/j.ijpe.2014.12.036.
[18]. W. Günther, M. H. R. Mehrizi, M. Huysman, and F. Feldberg, "Debating big data: A literature review on realizing value from big data," Journal of Strategic Information Systems, vol. 26, no. 3, pp. 191–209, Sep. 2017, doi: 10.1016/j.jsis.2017.07.003.
[19]. N. Côrte-Real, T. Oliveira, and P. Ruivo, "Assessing business value of Big Data Analytics in European firms," Journal of Business Research, vol. 70, pp. 379–390, Jan. 2017, doi: 10.1016/j.jbusres.2016.08.011.
[20]. X. Wu, X. Zhu, G. Wu, and W. Ding, "Data mining with big data," IEEE Transactions on Knowledge and Data Engineering, vol. 26, no. 1, pp. 97–107, Jan. 2014, doi: 10.1109/tkde.2013.109.
[21]. C. Vogel, S. Zwolinsky, C. Griffiths, M. Hobbs, E. Henderson, and E. Wilkins, "A Delphi study to build consensus on the definition and use of big data in obesity research," International Journal of Obesity, vol. 43, no. 12, pp. 2573–2586, Jan. 2019, doi: 10.1038/s41366-018-0313-9.
[22]. K. Wu, C. Liao, M. Tseng, M. K. Lim, J. Hu, and K. H. Tan, "Toward sustainability: using big data to explore the decisive attributes of supply chain risks and uncertainties," Journal of Cleaner Production, vol. 142, pp. 663–676, Jan. 2017, doi: 10.1016/j.jclepro.2016.04.040.
[23]. R. M. P, S. Ponnan, S. Shelly, Md. Z. Hussain, M. Ashraf, and A. Haldorai, "Autonomous navigation system based on a dynamic access control architecture for the internet of vehicles," Computers and Electrical Engineering, vol. 101, p. 108037, Jul. 2022, doi: 10.1016/j.compeleceng.2022.108037.
[24]. S. Mohanty, M. Jagadeesh, and H. Srivatsa, "Extracting Value From Big Data: In-Memory Solutions, Real Time Analytics, And Recommendation Systems," in Apress eBooks, 2013, pp. 221–250. doi: 10.1007/978-1-4302-4873-6_8.
[25]. M. Spiteri and S.-N. C. Rundgren, "Literature review on the factors affecting primary Teachers' use of Digital Technology," Technology, Knowledge, and Learning, vol. 25, no. 1, pp. 115–128, Jul. 2018, doi: 10.1007/s10758-018-9376-x.
[26]. M. Huberty, "Awaiting the second big data revolution: from digital noise to value creation," Journal of Industry, Competition and Trade, vol. 15, no. 1, pp. 35–47, Feb. 2015, doi: 10.1007/s10842-014-0190-4.
[27]. D. R. Mandel, "A positive future for futures and foresight science needs fierce competition in the marketplace of ideas: A commentary on Fergnani and Chermack 2021," Futures & Foresight Science, vol. 3, no. 3–4, Mar. 2021, doi: 10.1002/ffo2.67.
[28]. A. H and A. R, "Artificial Intelligence and Machine Learning for Enterprise Management," 2019 International Conference on Smart Systems and Inventive Technology (ICSSIT), Nov. 2019, doi: 10.1109/icssit46314.2019.8987964.
[29]. S. Akter and S. F. Wamba, "Big data analytics in E-commerce: a systematic review and agenda for future research," Electronic Markets, vol. 26, no. 2, pp. 173–194, Mar. 2016, doi: 10.1007/s12525-016-0219-0.
[30]. Z. Zhou, C. Xu, E. Li, L. Zeng, K. Luo, and J. Zhang, "Edge Intelligence: Paving the last mile of artificial intelligence with edge computing," Proceedings of the IEEE, vol. 107, no. 8, pp. 1738–1762, Aug. 2019, doi: 10.1109/jproc.2019.2918951.
[31]. M.-A. Vasile, F. Pop, R.-I. Tutueanu, V. Cristea, and J. Kołodziej, "Resource-aware hybrid scheduling algorithm in heterogeneous distributed computing," Future Generation Computer Systems, vol. 51, pp. 61–71, Oct. 2015, doi: 10.1016/j.future.2014.11.019.
[32]. J. Hu, H. Niu, J. Carrasco, B. Lennox, and F. Arvin, "Voronoi-Based Multi-Robot Autonomous Exploration in Unknown Environments via Deep Reinforcement Learning," IEEE Transactions on Vehicular Technology, vol. 69, no. 12, pp. 14413–14423, Dec. 2020, doi: 10.1109/tvt.2020.3034800.

[33]. M. E. Morocho-Cayamcela, H. Lee, and W. Lim, "Machine learning for 5G/B5G mobile and wireless communications: potential, limitations, and future directions," IEEE Access, vol. 7, pp. 137184–137206, Jan. 2019, doi: 10.1109/access.2019.2942390.
[34]. Z. Li, S. Bahramirad, A. Paaso, and M. Yan, "Blockchain for decentralized transactive energy management system in networked microgrids," The Electricity Journal, vol. 32, no. 4, pp. 58–72, May 2019, doi: 10.1016/j.tej.2019.03.008.
[35]. K. Cao, Y. Liu, G. Meng, and Q. Sun, "An overview on edge computing research," IEEE Access, vol. 8, pp. 85714–85728, Jan. 2020, doi: 10.1109/access.2020.2991734.
[36]. P. Leitão, A. W. Colombo, and S. Karnouskos, "Industrial automation based on cyber-physical systems technologies: Prototype implementations and challenges," Computers in Industry, vol. 81, pp. 11–25, Sep. 2016, doi: 10.1016/j.compind.2015.08.004.
[37]. S. Kıranyaz, O. Avcı, O. Abdeljaber, T. İnce, M. Gabbouj, and D. J. Inman, "1D convolutional neural networks and applications: A survey," Mechanical Systems and Signal Processing, vol. 151, p. 107398, Apr. 2021, doi: 10.1016/j.ymssp.2020.107398.
[38]. S. L. Smith, "The Contract Net Protocol: High-Level communication and control in a distributed problem solver," IEEE Transactions on Computers, vol. C–29, no. 12, pp. 1104–1113, Dec. 1980, doi: 10.1109/tc.1980.1675516.
[39]. A. Munir, E. Blasch, J. Kwon, J. Kong, and A. Aved, "Artificial intelligence and data fusion at the edge," IEEE Aerospace and Electronic Systems Magazine, vol. 36, no. 7, pp. 62–78, Jul. 2021, doi: 10.1109/maes.2020.3043072.
[40]. A. Haldorai, A. Ramu, and S. Murugan, "Smart Sensor Networking and Green Technologies in Urban Areas," Computing and Communication Systems in Urban Development, pp. 205–224, 2019, doi: 10.1007/978-3-030-26013-2_10.