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The application of industry 4.0 technologies in pandemic management: Literature review and case study

Javid Moosavi ^a, Javad Bakhshi ^{b,*}, Igor Martek ^c

^a School of the Built Environment, University of Technology Sydney, Sydney 2007, Australia

^b School of Project Management, The University of Sydney, Sydney 2006, Australia

^c School of Architecture and Built Environment, Deakin University, Geelong VIC 3220, Australia

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ABSTRACT

The Covid-19 pandemic impact on people's lives has been devastating. Around the world, people have been forced to stay home, resorting to the use of digital technologies in an effort to continue their life and work as best they can. Covid-19 has thus accelerated society's digital transformation towards Industry 4.0 (the fourth industrial revolution). Using scientometric analysis, this study presents a systematic literature review of the themes within Industry 4.0. Thematic analysis reveals that the Internet of Things (IoT), Artificial Intelligence (AI), Cloud computing, Machine learning, Security, Big Data, Blockchain, Deep learning, Digitalization, and Cyber-physical system (CPS) to be the key technologies associated with Industry 4.0. Subsequently, a case study using Industry 4.0 technologies to manage the Covid-19 pandemic is discussed. In conclusion, Covid-19 is clearly shown to be an accelerant in the progression towards Industry 4.0. Moreover, the technologies of this digital transformation can be expected to be invoked in the management of future pandemics.

1. Introduction

The impact of Covid-19 on the world has been catastrophic. To date (August 2021), 170 million people have been infected, and 3.5 million people have lost their lives. The impact extends well beyond individual fatalities, adversely affecting families and whole communities. The WHO's first media statement, in 2019, referred to viral pneumonia, but by March 2020, after spreading to 120 countries, a pandemic was declared [1]. To reduce the spread, governments enacted restrictions such as quarantine, self-isolation, stay-at-home edicts, and other measures [2]. By April 2020, more than four billion people globally had been ordered to stay at home [3]. The stay-at-home decrees led to immense changes in how people work and live. Working from home is no longer an unusual concept, with people adapting to the change with advanced technologies. The Covid-19 pandemic changed the world, and many of these changes are here to stay. A study by Jost et al. [4] confirms that Covid-19 has accelerated the adoption of digital and intelligent technologies. Findings reveal far-reaching shifts in industry managers' mindsets on the use of advanced technologies.

The first industrial revolution used water and steam power to mechanize production. The second used electric power, making mass production possible. The third used electronics and information technology to modernize production. The fourth industrial revolution, known as industry 4.0, is an IT-driven digital transformation that enhances machine-human correlation to advance system self-optimization [5].

The Covid-19 pandemic has accelerated this digitalization paradigm along with the use of Industry 4.0's emerging technologies. This digital revolution contains many new initiatives and technologies. A range of studies has investigated specific technologies in general or how these impact specific industries. However, broader research that identifies and describes Industry 4.0 technologies in the wake of Covid-19 remains to be undertaken. This study aims to bridge that gap by undertaking a literature review in order to identify emerging themes in Industry 4.0 and assess their specific contribution to the field of disaster management.

In pursuing this line of inquiry, this study aims to answer the following questions:

(RQ1) What are the key emerging technologies and concepts in industry 4.0?

(RQ2) How can these emerging technologies contribute to the management of a pandemic?

There are a number of existing scientometric analyses on industry 4.0, e.g., [6–9], focusing on specific industries, i.e., manufacturing and supply chain. They do not, however, consider the Covid-19 issue. This study, by contrast, is not restricted to a specific industry but aims rather identify all relevant technologies. Moreover, this study is the first to employ network and thematic analysis in order to identify emerging technology themes, moving on to review the applicability of

* Corresponding author.

E-mail addresses: Seyedjavid.mousavi@uts.edu.au (J. Moosavi), javad.bakhshi@sydney.edu.au (J. Bakhshi), igor.martek@deakin.edu.au (I. Martek).

those technologies in alleviating the debilitating effects of the Covid-19 pandemic through case studies.

The remainder of the paper is organized as follows. The research method is explained in Section 2; the findings and discussion are presented in Section 3; the case study is discussed in Section 4; with closing comments in Section 5.

2. Research method

The research method adopted in this study is undertaken in two phases. First, a comprehensive literature review of journal articles dealing with Industry 4.0-related topics is conducted. In the second stage, a case analysis is presented of the Australian government’s use of Industry 4.0 technologies in managing the Covid-19 outbreak.

2.1. A comprehensive literature review of industry 4.0 publications

A systematic literature review is a research approach applied to identifying, evaluating, and synthesizing related publications on a topic [10]. It can be run in an interdisciplinary field (e.g., engineering and management). However, different approaches exist in conducting literature reviews, with no unequivocal methodology established for literature reviews in management sciences [11]. Notwithstanding, scientometric analysis is commonly used across different sectors of management, such as operations research [12], supply chain management [13], construction management [14], and project management [15]. Moosavi et al. [16] used a three-step scientometric analysis approach, incorporating keyword selection, bibliometric, and citation analysis. Likewise, this study follows that accepted precedent. Results obtained from the analysis are evaluated, and the research questions are answered.

Researchers have applied Citation-based analyses to identify primary trends and evaluate field study patterns [17]. The Citation-based analysis is a publications analysis tool for identifying the primary contributors [17,18]. Three primary tools deliver the citation-based analysis: citation analysis, bibliographic coupling, and co-citation analysis [16,19]. Some researchers have questioned the accuracy of direct citation and bibliometric coupling [20]. Nevertheless, co-citation analysis is accurate and thus widely used [21]. Moreover, co-citation analysis is appropriate for evaluating interdisciplinary studies [22] such as industry 4.0. It is for this reason that co-citation analysis is employed here.

2.1.1. Literature search protocol

On the 2nd of March 2021, we conduct the data set research. Both the well-known databases, Scopus and Web of Science, were considered and piloted. Results confirmed that Scopus captured all the Web of Science records, though this did not hold the other way around. Consequently, the search proceeded with Scopus as the database. The initial research on industry 4.0 resulted in approximately 18000 records; The one-step search was applied in the Document category. Due to the high yield of publications, the source qualifiers, Conference Paper, Review, Book Chapter, Conference Papers, Article in Press, Conference Proceeding, Book Series, Trade Journals, Undefined, and non-English language texts, were excluded. In addition, it is limited to the Covid-19, and after further inspection for relevance, 931 article records were retained and set as the basis for a bibliometric and network analysis.

The term Industry 4.0 was coined in 2011 by Dr. Wolfgang [23,24]; thus, Industry 4.0 publications begin from that year. From 2015, publications began to double every year as a result of the seminal work by Klaus Schwab [25]. The exponential growth in research activity affirms the increasing interest of researchers, scholars, and practitioners in this emergent field.

Table 1
Most repeated keyword.

| Keywords | Frequency | Degree centrality | Betweenness | Relative importance |
|-------------------------|-----------|-------------------|-------------|---------------------|
| Internet of things | 246 | 2684 | 3052357 | 1 |
| Artificial intelligence | 120 | 748 | 305177 | 2 |
| Cloud computing | 63 | 344 | 113237 | 3 |
| Machine learning | 58 | 341 | 6741 | 4 |
| Security | 40 | 277 | 72285 | 5 |
| Big data | 59 | 253 | 69481 | 6 |
| Blockchain | 42 | 239 | 4529 | 7 |
| Deep learning | 43 | 228 | 78756 | 8 |
| Digitalization | 12 | 118 | 118795 | 9 |
| Cyber-physical system | 37 | 98 | 15252 | 10 |
| Automation | 13 | 87 | 53468 | 11 |
| Digital twin | 11 | 73 | 33809 | 12 |
| Smart manufacturing | 18 | 45 | 7739 | 13 |
| Augmented reality | 7 | 38 | 23122 | 14 |
| Additive manufacturing | 8 | 35 | 0 | 15 |
| Simulation | 6 | 23 | 2297 | 16 |

2.2. Case study: the Australian government COVID safe service

This section explores the role of emerging Industry 4.0 technologies in pandemic management, particularly in response to the Covid-19 outbreak. It is a descriptive qualitative analysis based on secondary data. The data and information used in this case study were obtained from the project reports and the minutes of the Department of Health meetings of the Australian federal and local governments. Monitoring and daily assessment reports produced by Departments of Health were also used [26].

3. Findings and discussion

In this section, we conduct the bibliometric, citation analysis, and theoretical background and keywords’ definitions. First, we part perform bibliometric analysis aiming to obtain primary themes. Secondly, we implement citation analysis to obtain influential studies. Then we discuss the keywords’ definition.

3.1. Bibliometric analysis

Keywords characterize the issues of concern in a document [27]. Accordingly, the objective is to extract the keywords by selecting the Co-occurrence analysis in VOSviewer [28]. Retrieved keywords and their frequency, degree of centrality, betweenness, and relative importance are tabulated in Table 1. The search keyword (Industry 4.0) is excluded from the results. Frequency refers to the count of occurrences and degree centrality to the count of links between the keywords. Betweenness degree indicates the extent to which a keyword mediates or falls between any other two keywords on the shortest path between those two keywords; usually averaged across all possible pairs in the network [29]. "Internet of Things" (IoT) is the most repeated keyword, following by 'Artificial Intelligence' (AI), 'Cloud computing', 'Machine learning', 'Security', 'Big Data', 'Blockchain', 'Deep learning', 'Digitalization', and 'Cyber-physical system' (CPS) are feature as keywords.

This study proceeded by running the keyword’s network analysis. The network of the primary keywords is shown in Fig. 1, where the circles’ size reflects the keyword occurrence frequency, while the link’s size and length between the circles illustrate the relatedness of keywords [29].

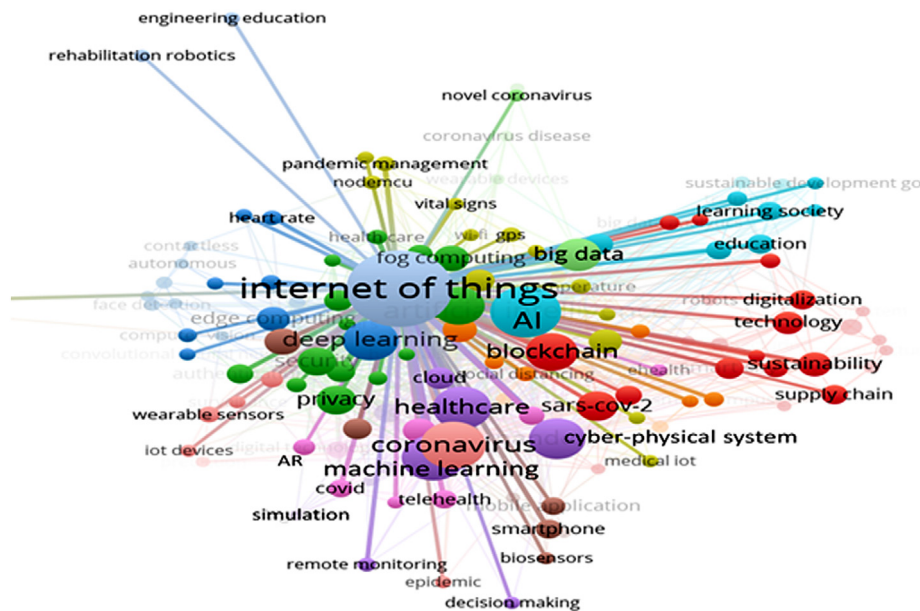


Fig. 1. Keyword network analysis.

Table 2
Top contributing industry 4.0 technologies.

| Cluster ID | Size | Silhouette value | Mean (year) | Dominate technologies |
|------------|------|------------------|-------------|-----------------------|
| 0 | 294 | 0.554 | 2013 | IoT |
| 1 | 198 | 0.611 | 2014 | Digitalization |
| 2 | 136 | 0.685 | 2015 | Big data |
| 3 | 43 | 0.769 | 2016 | AR-VR |
| 4 | 12 | 0.997 | 2004 | Smart factory |
| 5 | 10 | 0.978 | 2017 | AI |
| 6 | 7 | 0.999 | 2010 | Machine learning |
| 7 | 6 | 1 | 2018 | Cloud |

3.2. Citation analysis

The CiteSpace [30] is used to run citation analysis for identifying the highly cited articles as references, shown in Fig. 2. The articles are reviewed to determine their central topics. The citation analysis findings support the previous section’s (bibliometric analysis) findings where IoT, CPS, Cloud, and Digitalization are among the most highly ranked.

Next, a co-citation analysis was run, which yielded eight clusters: IoT, Digitalization, Big Data, AR-VR, Smart Manufacturing, AI, Machine Learning, and Cloud, again, where IoT dominates the primary topics, as shown in Fig. 3.

The details of the clusters are tabulated in Table 2, where the Silhouette value is the measure within the -1 to +1 range and refers to the similarity of an item to its cluster. The higher this value count, the more the similarity to its cluster, with fewer matches to neighbor clusters [31]. The Category refers to the previous section’s conceptual model categories.

3.3. Theoretical background and keywords’ definitions

Industry 4.0 is the fourth industrial revolution and is an IT-driven digital transformation that enhances machine-human correlation to advance system self-optimization [5]. The primary goal of industry 4.0 is to improve efficiency and productivity by data-driven automation in a real-time manner [32]. These disruptive transformation features in Industry 4.0 include automation, digitization, human-machine interaction, automatic data exchange, and communication [33]. These features

are highly related to optimization algorithms and internet technologies. Industry 4.0 refers to a wide range of concepts and emerging technologies like the IoT, CPS, AI, Digitization, and Automation [32,34,35]. In brief, Industry 4.0 is an IT-driven transformation to make systems more resilient and intelligent in a real-time manner [34].

In the following, we define the primary topics and technologies of industry 4.0, which resulted from the scientometric analysis.

IoT stands for the Internet of Things, a global network of devices [36]. An interrelated system of connected devices, objects, humans, and animals that can interact. These corresponding elements are connected through the internet by the embedded sensors and software therein. IoT facilitates real-time data collection and information sharing, a primary notion of industry 4.0 [36,37]. IoT devices facilitate a high-speed interaction between devices that enhance automation and reduce human interface. In the context of COVID-19, different research themes have been conducted that benefited from IoT—for instance, controlling and spreading prediction of Coronavirus [38–40], smart diagnostics [41,42], and home hospitalization [43].

Artificial Intelligence refers to machine acts that mimic human intelligence like problem-solving and learning. Artificial Intelligence enables machines and systems to draw decisions and act like a human. The impact of AI on different sectors like finance [44], banking [45], autonomous vehicles [46], health [47], knowledge management, and decision science [48] is evident and indisputable. Artificial Intelligence reduces human errors [49], automates repetitive tasks, and is available 24/7 [50]. AI is a vital part of Industry 4.0 that covers extensive areas like machine learning, deep learning, digitization, and automation. AI helps to accurate diagnosis [51–53], virology [54,55], telemedicine [56,57], and procedures [58,59].

Cloud computing is the Internet-based enterprise services and applications like data storage, servers, and software [60]. It is an emerging paradigm for companies that seek to convert from a physical network and servers to an advanced cloud-based infrastructure. Cloud computing offers the three: Software as Service (Saas), Platform as Service (Paas), and Infrastructure as Service (Iaas) service models [61]. The outstanding examples of these services are categorized in a pyramid in Fig. 4. Selecting the proper service model depends on the given business’s requirements. These services are not without their advantages and disadvantages, while cloud computing generally enhances

| References | Topic | Year | Strength | Begin | End | 2010 - 2021 |
|---------------------------|-----------------------|------|----------|-------|------|-------------|
| Bauernhansl et al. (2014) | Smart factory | 2014 | 8.26 | 2015 | 2018 | |
| Kagermann (2013) | Digitalization | 2013 | 15.6 | 2016 | 2017 | |
| Brettel et al. (2014) | Smart manufacturing | 2014 | 15.52 | 2016 | 2018 | |
| Xu (2012) | Cloud | 2012 | 12.64 | 2016 | 2018 | |
| Wang et al. (2016) | Smart factory | 2016 | 9.42 | 2016 | 2018 | |
| Lee (2008) | Cyber physical system | 2008 | 8.4 | 2016 | 2017 | |
| Lee et al. (2015) | Cyber physical system | 2015 | 14.89 | 2017 | 2018 | |
| Wan et al. (2016) | IoT | 2016 | 10.56 | 2017 | 2018 | |

Fig. 2. Top 8 articles with the strongest citation bursts in the Industry 4.0.

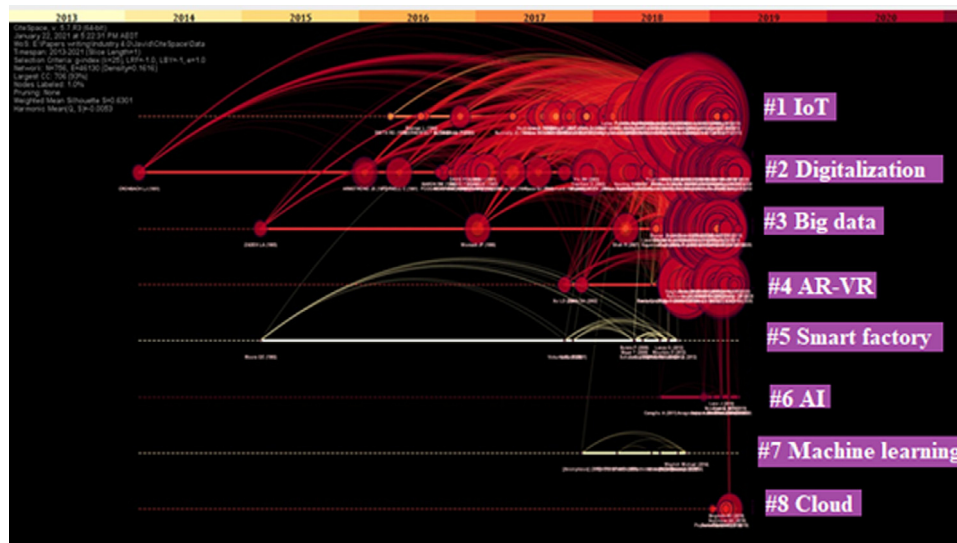


Fig. 3. Co-citation analysis.

their security and mobility. COVID-19 outbreak [62], patient management [63,64], monitoring systems [65,66] are considered in this section.

Machine learning is a subset of AI that enables a system to learn and act like a human. An intelligence system needs to learn and provide an enhanced result compared to the previous experience (data). Machine learning solves problems by learning from experienced data and improving it without being explicitly programmed [70]. It analyses the situation, recognizes the pattern, and provides a proper solution [71]. Machine learning has been and is widely applied in different sectors like manufacturing, telecommunication, and finance. Alpaydin [70] reveals that machine learning could analyze manufacturing process problems and optimize production operation. It recognizes the telecommunication patterns and provides an optimum network and data distribution. As to finances, analyses the customer’s past data to construct a model in credit applications. Detection of COVID-19 [72,73], prediction of epidemic trends [74,75], and COVID-19 forecast [76,77] have employed machine learning.

Security is a primary challenge in the realm of Industry 4.0 [78]. Industry 4.0 is a data-driven transformation with high reliance on information sharing. Due to the interconnected nature of Industry 4.0, all the devices, machines, and operations are connected by an internet

network, making the system highly vulnerable to cyber-attacks [79]. Consequently, cyber and network security are two of the crucial challenges in Industry 4.0. According to Lezzi et al. [80], Industry 4.0’s security is of the four main: cyber-attack, system vulnerabilities, cyber threats, and risks themes, where the cyber threats can affect the three: execution (e.g., sensors and actuators), data transport, (e.g., network), and application control, (e.g., user data storage) layers. Insecurity and mental health [81,82], privacy and Security [83,84] and social security [85,86] are popular research themes here.

Big data is a complex, large and diverse data set generated from multiple autonomous sources [87]. This data is extremely complicated to be processed with general data-processing methods. Data scientists use particular methods to transform this complicated data to be used. Big data analysis recognizes the patterns and visualizes the data to draw meaningful insight for decision-makers [88]. Monitoring cases [89,90], coronavirus infections [91], and virus transmission [92] are the most popular area of research in this domain.

Blockchain is a distributed database of digital transactions and ledgers in a peer-to-peer network that provides a decentralized and immutable set of records and information among participants [93]. Blockchain is a set of information blocks containing the data, hash, and the previous block’s hash [94]. Hash is a set of unique symbols that

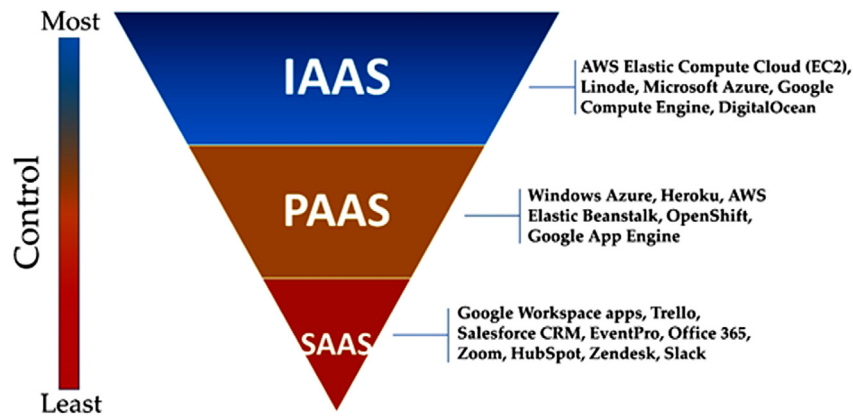


Fig. 4. Three major cloud categories [67].

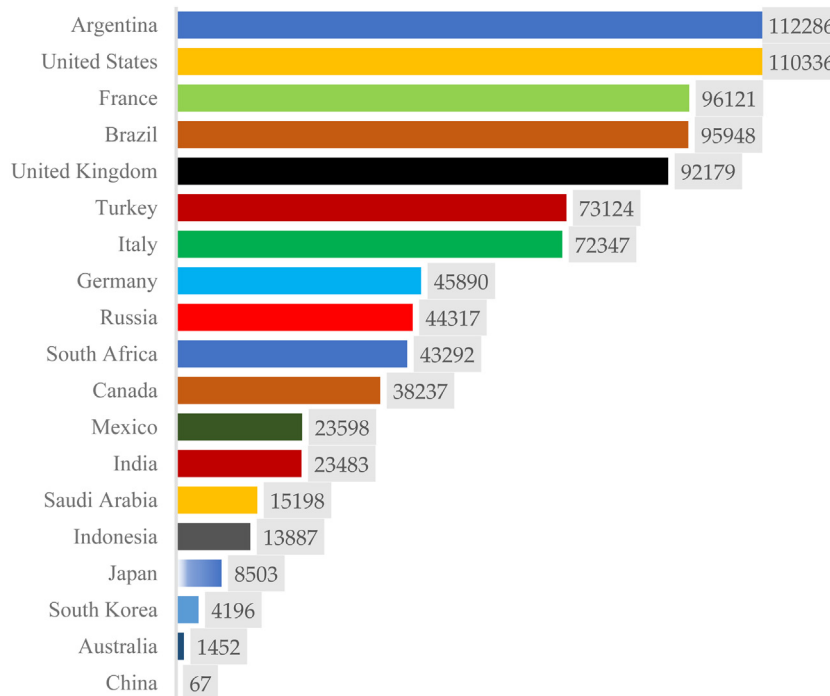


Fig. 5. The G20 total confirmed COVID-19 cases per million people (Last update: the 11th of August, 2021) Note: Raw data on confirmed cases for all countries is sourced from the COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University.

identify the blocks. Blockchain was initially introduced as a financial transaction procedure named bitcoin. It extended into other sectors like manufacturing [93], transport and logistics [95], and supply chain management [16,96]. Blockchain contributes to transparency [97,98], contact tracing models [99,100], and digitalization of money in the post-Covid [101].

Deep learning is a subset algorithm of machine learning categorized in AI inspired by the human brain neural network. The deep neural network of the brain enables one to learn from experience; likewise, a deep learning algorithm generates experiments, learns, and improves the practice at each run [102]. However, the quantity and quality of the input data are crucial. Sufficient and proper data in deep learning is similar to the extensive human experience in drawing mature decisions. Appropriate data enables the algorithm to improve the outcome, leading to a better decision [103]. Deep learning could reduce or eliminate human interactions, thus, the AI's objective. Managing clinical

practice [104], medicines [105,106], diagnosis [107,108], and patients management [109,110] have highlighted the role of deep learning.

Digitalization is the transformation paradigm from the physical to the virtual world. This transformation requires the Digitalization of the physical items and operations into data which is the input of emerging technologies. According to Kagermann [111], Digitalization changes all organizational status by underlying digital transformation and contributing to sustainability.

Cyber-physical system (CPS) is the integration of software and hardware to perform a task. It is an integrated system of computation and computers to sense, control, and monitor physical processes [112]. According to [113], CPS is an embedded technology that enables a system to respond to the real world. It is highly contributive to transportation management systems. Massachusetts Institute of Technology implemented a project named CarTel, which collects data from mobile sensors, visualizes and analyses it to mitigate traffic, monitor road surface, and detect hazards [114]. The cyber-physical system's objective is to minimize human interaction and operate the system autonomously.

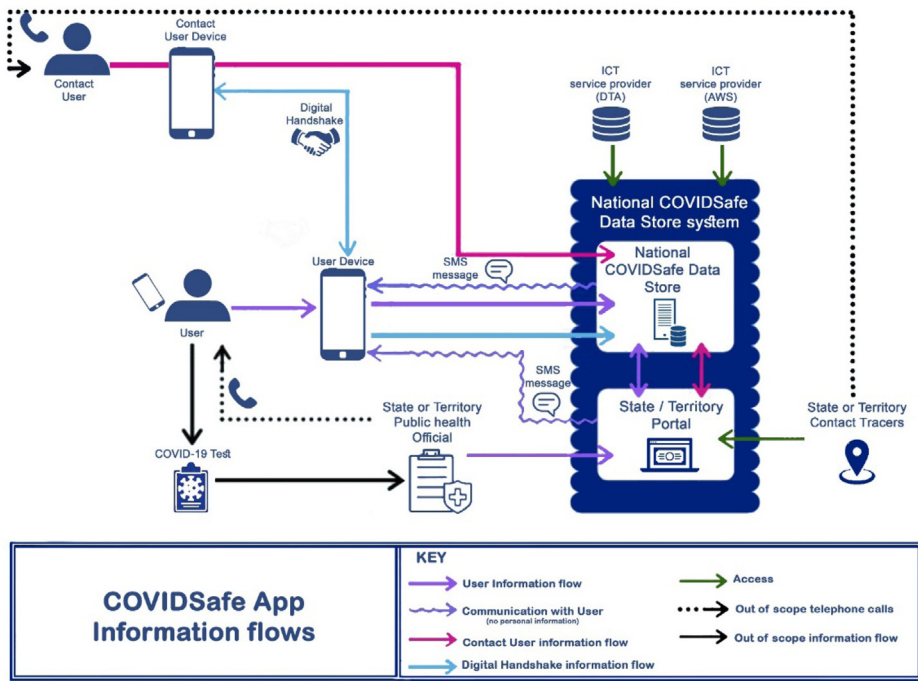


Fig. 6. COVIDSafe mobile application information flow [68,69].

After the coronavirus outbreak, vaccine supply chain resilience and risks [115–117] and post-COVID digital manufacturing [118,119] are the most common research area of cyber–physical systems.

Automation is one of Industry 4.0’s ultimate objectives, aiming to automate processes as much as possible to decrease human interaction [120,121]. Less human interaction could reduce human errors, thus reducing cost and increasing efficiency [122]. Health care facilities and equipment [58,123], and COVID testing [124,125](Bonelli et al. 2020; Hirotsu et al. 2020) are common research themes in this area.

Smart manufacturing refers to digitized manufacturing that collects and shares real-time data to optimize production processes [126]. The objective of smart manufacturing is to operate the entire production system with minimum human interaction in an autonomous manner. Self-optimization, self-learning, and adaptation with constraints by implementing AI are pursued in smart manufacturing [127]. This objective could be met by applying the embedded systems like IoT, CPS, Big Data, and Cloud Computing [31]. Sustainable and resilient manufacturing is getting more attention from researchers after the global pandemic [128,129].

Augmented Reality (AR) is the computer-generated existence of objects, augmented with the real-world physical environment [130]. This technology expands the physical world experience through the digital information layers. After introducing this technology, it was and is widely applied in the game industry. Now it is being applied in many other sectors, like education [131] and high-risk industries [132,133], etc. It enables individuals to monitor and control dangerous operations without being physically involved. It also contributes to expensive and sensitive equipment training [132]. Augmented reality contributes to the post-covid 19 tourisms [134,135], and medical education [136, 137] after Coronavirus.

Simulation is the digital twin brother of the physical world that mimics the physical operation and processes. It is a cost-effective approach applied in modeling, analyzing, and testing complicated processes that enable companies to evaluate a procedure’s risk and cost before its actual implementation. Simulation has been and is being run widely by scholars and practitioners in different sectors like manufacturing [138], education [139], supply chain management [140],

project management [141], construction engineering and management [142], etc. The exemplary simulations; discrete event, continuous event, Monte Carlo, and system dynamics. According to Jahangirian et al. [138], the most popular simulation is the discrete-event; though its stakeholder engagement is lower than its counterparts, the system dynamics in specific. Virus Pneumonia [143,144], control techniques [145], smart healthy city [146,147], and vaccination [148,149] are considered simulation and digital twin.

4. Case study (CovidSafe Mobile App and COVID Safe Check-in)

This section illustrates how the technologies that appeared in the previous section can be used in a pandemic. The following case study discusses two classes of technologies used in Australia to manage the Covid-19 pandemic.

Australia is one of only a few countries with any success regarding pandemic management. Death rates have significantly been contained, particularly when compared to the rest of the world, mainly Europe, the United States, the UK, India, and Indonesia [150]. Fig. 5 depicts the Covid-19 status in Australia compared to the other G20 countries. Real-time data continues to be a vital tool in managing the pandemic [150, 151]. According to McKinsey [152], data-driven decision-making is a particular Australian success factor in managing the pandemic. Two aspects of the Australian case are worthy of attention: the CovidSafe Mobile App and COVID Safe Check-in. Both exhibit great potential as emerging technologies fit for managing the Covid-19 pandemic.

The CovidSafe Mobile App is a contact tracing mobile application that identifies people exposed to the coronavirus (Covid-19). This app runs on Bluetooth, pairing with others who have installed it. When people are in proximity with one another, the app takes note of the contacted user’s phone model, distance, time, and date through a digital handshake process [68]. See Fig. 6. The COVIDSafe does not record one’s location [69]. The information is encrypted and stored securely on the applicant’s phone for twenty-one days (fourteen days for virus incubation, plus seven days to receive test results). If someone tests positive, after receiving the subject’s consent, the digital handshake information is uploaded for data storage, allowing the health authorities to contact whoever had close contact with the subject and prescribes

Table A.1
Percentage of top research themes over the time in Industry 4.0 literature.

| 2011 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|------------------------------|-----------------------------------|-------------------------------|---------------------------------|--------------------------------------|--|---------------------------------|---------------------------------|--------------------------------|
| Internet of things (100%) | Internet of things (66.67%) | Industry 4.0 (30%) | Industry 4.0 (46.77%) | Industry 4.0 (40.25%) | Industry 4.0 (50.13%) | Industry 4.0 (46.29%) | Industry 4.0 (41.62%) | Industry 4.0 (38.5%) |
| Information collecting (50%) | Energy efficiency (33.3%) | Manufacturing (20%) | Internet of things (16.12%) | Internet of things (25.32%) | Internet of things (16.17%) | Internet of things (40%) | Internet of things (38.5%) | Internet of things (32.6%) |
| Performance analysis (50%) | Duty cycle (33.3%) | Internet of things (15%) | Industrial internet (14.51%) | Cyber physical systems (18.18%) | Cyber physical system (14.05%) | Smart factory (11.45%) | Smart factory (13.15%) | Smart factory (11%) |
| Scheduling algorithm (50%) | Sensor communication (33.3%) | Cloud computing (10%) | Cyber physical systems (11.29%) | Smart factory (11.68%) | Smart factory (12.46%) | Cyber physical systems (7.90%) | Cyber physical systems (11.30%) | Machine learning (9.5%) |
| Machine tool (50%) | Time synchronized channel (33.3%) | Knowledge management (10%) | Big data (9.67%) | Manufacturing (8.44%) | Industrial Internet of things (11.93%) | Manufacturing (6.77%) | Machine learning (8.8%) | Blockchain (8.2%) |
| | | Wireless communication (10%) | Cloud computing (8.06%) | Digitalization (7.79%) | Manufacturing (9.01%) | Big data (5.80%) | Blockchain (7.18%) | Digital twin (6.2%) |
| | | Cloud computing (10%) | Information (8.06%) | Virtualization (5.84%) | Digitalization (8.48%) | Cloud computing (5.48%) | Big Data (7.11%) | Big Data (6.2%) |
| | | Communication standards (10%) | Smart factory (8.06%) | Big Data (5.19%) | Big data (6.36%) | Robotics (4.67%) | Artificial Intelligence (6.85%) | Cyber-physical system (5.8%) |
| | | | Business (8.06%) | Automation (4.54%) | Cloud computing (6.10%) | Sustainability (4.35%) | Scheduling (5.30%) | Edge computing (5.4%) |
| | | | Human resource (6.45%) | Control system (4.54%) | Robotics (5.03%) | Security (3.87%) | Supply chain (5.30%) | Security (4.1%) |
| | | | Manufacturing (6.45%) | Production management (3.89%) | Machine learning (4.77%) | Digitalization (3.70%) | Security (4.80%) | Artificial intelligence (4.1%) |
| | | | Visual computing (6.45%) | Quality system (3.89%) | Automation (4.24%) | Data analysis (3.38%) | Cloud computing (4.54%) | Deep learning (4.1%) |
| | | | Computer graphics (4.83%) | Energy management (3.24%) | Human factors (3.44%) | Supply chain management (3.38%) | Simulation (4.12%) | Sustainability (3.9%) |
| | | | Flexibility (4.83%) | Industrial wireless networks (3.24%) | Sensors (3.44%) | Software (3.06%) | Automation (4.12%) | Predictive maintenance (3.3%) |
| | | | Machine learning (4.83%) | flexible manufacturing (2.59%) | Sustainability (3.44%) | Technology (3.06%) | Process monitoring (3.96%) | Cloud manufacturing (3.2%) |
| | | | Automation (4.83%) | Industrial Internet (2.59%) | Knowledge management (3.18%) | Energy optimization (2.90%) | Digitization (3.36%) | supply chain (3%) |
| | | | Computer vision (3.22%) | RFID (2.59%) | Lean production (3.18%) | Machine learning (2.90%) | Deep learning (2.96%) | Cloud computing (3%) |
| | | | Energy management (3.22%) | Security (2.59%) | Simulation (2.91%) | Wireless sensor network (2.90%) | Energy efficiency (2.96%) | Augmented reality (2.5%) |
| | | | Intelligent system (3.22%) | Automotive industry (1.94%) | Innovation (2.65%) | Fog computing (2.74%) | Fault diagnosis (1.9%) | Anomaly detection (2.2%) |
| | | | Knowledge (3.22%) | Cloud computing (1.94%) | Network (2.65%) | Simulation (2.74%) | Augmented reality (1.9%) | Digitalization (2.2%) |

directives. This mobile application benefits from primary Industry 4.0 features, i.e., IoT and CPS to collect data, encryption (Blockchain) for security, along the Cloud to manage it. AI could use this big data in recognizing spread patterns. These technologies build a system able to identify high-risk people in real-time. Faster tracking of positive cases would facilitate the rapid reaction, contributing to the system's resilience against the pandemic [153].

COVID Safe Check-in is an electronic registration tool. This tool provides a quick check-in for people visiting public places. Two million people have already installed the app, 100,000 businesses registered customers through the app, and 32 million check-ins were recorded [154]. People are asked to check-in by scanning the QR code displayed on a business or facility entrance and uploading contact

information. If the subject tests positive, the health authorities contact whoever has been in the same place where the person was. This data-driven tool accelerates the speed of contacting and tracing people exposed to the virus, which is vital to pandemic management [150].

In brief, the Australian government developed two mobile applications that facilitate the tracking of positive coronavirus cases. These apps enable the authorities to contact people quickly and ask them to self-isolate immediately and get tested. The process has proven effective in virus spread prevention [155,156]. These Industry 4.0 technologies demonstrate the potential of Industry 4.0 solutions to mitigate the debilitating health and other effects of the Covid-19 pandemic.

5. Conclusion

Several literature reviews have been conducted on Industry 4.0. A comprehensive non-sector focused approach utilizing a scientometric analysis had, however, yet to be undertaken. Moreover, there is no bibliometric and citation analysis on Industry 4.0 that describes the capacity of Industry 4.0 to facilitate pandemic management. This study addresses this gap. It maps Industry 4.0's primary technologies through a systematic literature review. It also explores their application in managing the pandemic through the Australian Covid-19 experience.

Findings reveal that publications have almost doubled over the last five years. The bibliometric and network analysis also reveals IoT, Big Data, AI, Machine Learning, Cloud, Blockchain, Deep learning, CPS, Augmented Reality, and Digitalization to be the main topics and technologies of Industry 4.0, with results confirmed by network analysis.

Industry 4.0 offers technologies that have the potential to contribute to pandemic management. Specifically, IoT and CPS facilitate data collection of infected cases, encrypting them with Blockchain-enabled technologies and then storing them in the Cloud. Afterward, these big data are available for interpretation by AI from which meaningful insights with implications for policy-makers may be drawn. The Australian mobile applications discussed in the case study are confirmed as effective technology-supported management tools that have had significant, measurable positive impacts in containing the Covid-19 outbreak.

As the case study was undertaken on Australia's Covid-19 pandemic management, this represents one of the limitations of the study. In future studies, the approach taken here provides a template by which further research may be conducted in the context of other countries, characterized by their own different features and experiences arising from the Covid-19 pandemic. Moreover, this study is based on secondary data analysis, presenting as a barrier to the identity of specific Industry 4.0 technology interventions. Assessing how each of the specific technologies would contribute to mitigating the effects of the Covid-19 pandemic is of major interest, to be taken up in future studies.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See Table A.1.

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