Are Metaverse Applications in Quality 4.0 Enablers of Manufacturing Resiliency? An Exploratory Review Under Disruption Impressions and Future Research

Abstract

Purpose: The purpose of this paper is to investigate, from a thorough review of the literature, the role of metaverse-based quality 4.0 (MV-based Q4.0) in achieving manufacturing resilience (MFGRES). Based on a categorization of MV-based Q4.0 enabler technologies and MFGRES antecedents, the paper provides a conceptual framework depicting the relationship between both areas while exploring existing knowledge in current literature.

Design/methodology/approach: The paper is structured as a comprehensive systematic literature review (SLR) at the intersection of MV-based Q4.0 and MFGRES fields. From the Scopus database up to 2023, a final sample of 182 papers is selected based on the inclusion/exclusion criteria that shape the knowledge base of the research.

Findings: In light of the classification of reviewed papers, the findings show that artificial intelligence is especially well suited to enhancing MFGRES. Whereas transparency and flexibility are the resilience enablers that gain most from the implementation of MV-based Q4.0. Through analysis and synthesis of the literature, the study reveals the lack of an integrated approach combining both MV-based Q4.0 and MFGRES. This is particularly clear during disruptions.

Research limitations/implications: This study addresses only the Scopus database. Furthermore, further empirical study on the subject needs to be added to this study. Within the same research domain, it would be interesting to evaluate the effect of MV-based Q4.0 on MFGRES. Instead of concentrating solely on the Scopus database as in this paper, researchers may also need to investigate the various databases more broadly while using different keywords.

Practical implications: This study has a significant impact on managers and businesses. It also advances knowledge of the importance of MV-based Q4.0 in achieving MFGRES and gaining its full rewards.

Originality/value: This paper makes significant recommendations for academics, particularly those who are interested in the metaverse concept within MFGRES. The study also helps managers by illuminating a key area to concentrate on for the improvement of MFGRES within their organizations. In light of this, future research directions are suggested.

Keywords: Metaverse, Manufacturing resilience, Disruption, Quality 4.0, Exploratory review

1. Introduction

Over the last quarter-century, major crises have taken many different forms, including terrorism, disease, natural disasters, insect invasion, war, and financial collapse (Dwaikat et al., 2022; A. Kumar et al., 2020). Future crises of various magnitudes will undoubtedly occur, such as the continuing effects of global warming (The New Humanitarian, 2023). While some crises have only affected a region's frontiers, others, including those affecting global supply chains (SC), have shook the entire world (Allam et al., 2022). However, no recent incident has brought attention to supply chains' vulnerability in the same way as the COVID-19 outbreak did at the beginning of 2020 (Belhadi et al., 2021; Njomane & Telukdarie, 2022). The majority of businesses encountered significant challenges in each SC section. Manufacturing was impacted by stricter hygiene regulations and plant closures, customer demand was incredibly unpredictable , and suppliers were unable to meet their delivery obligations (Allam et al., 2022; Belhadi et al., 2021). These circumstances are concerning because SC disruptions can have serious repercussions that directly impact the performance of the entire company (Belhadi et al., 2021, p. 19). Major outcomes include decreases in sales and market share, delays in delivery, and declines in quality of service and customer satisfaction that harm public image (Bianco et al., 2023, p. 19; Frieske & Stieler, 2022, p. 19; Njomane & Telukdarie, 2022). Potentially damaging brand effects extend beyond those SC members who are directly impacted. Due to the growth of social media, experiences due to bad manufacturing disruptions can now be quickly shared with a large audience, further harming a company's reputation (J. Yang et al., 2022).

The fourth industrial revolution, also known as Industry 4.0 (I4.0), is currently in full swing. Technology advances in data analytics, collaboration, networking, and scalability boost creativity and shift the paradigm in the production of items and services (Mahmoodi et al., 2022). In order to meet the major challenges relating to quality, Quality 4.0 (Q4.0) technologies are available to maintain standards during manufacturing (Javaid et al., 2021). Technology such as artificial intelligence, machine learning, big data, cloud computing, virtual reality, augmented reality, new materials, the IoT and more, have evolved as a result of the quality revolution for improved communication as well as preserving the quality of the manufacturing process (El Jaouhari, Alhilali, et al., 2022; Javaid et al., 2021).

Although the manufacturing sector is embracing Q4.0, the COVID-19 pandemic outbreak unexpectedly slowed the growth of the smart factory and the global supply chain (Njomane & Telukdarie, 2022). Because of the widespread lockdown, factories that depend on labor reduced or stopped production, severely disrupting the global supply chain (A. Kumar et al., 2020). In terms of COVID-19's expected effects on economic output, the International Labour Organization (ILO Monitor, 2020) anticipates that the manufacturing sector will suffer the most. A recent survey (Kamarthi & Li, 2020) of 558 respondents found that 78.3% of manufacturing businesses expect financial repercussions; 53.1% expect a change in operations, and 35.5% are dealing with disruptions in their supply chains.

In the actual technological era, where there are more possibilities of disrupting the manufacturing setting, the problem of manufacturing systems' resilience is even more important (Bianco et al., 2023; Kamarthi & Li, 2020). Moreover, COVID-19 sparked new revolutionary changes, accelerating the adoption of I4.0 technologies' adoption (Bianco et al., 2023). Countries with developing fully digital economies are thought to be built around digitalization innovations like distributed ledger technology (DLT), artificial intelligence (AI), metaverse (MV), and other emerging information communication technologies (ICT) (Bianco et al., 2023). I4.0 encompasses an extensive range of technologies that present a promising environment for metaverse applications (Cali et al., 2022). A previously unexplored metaverse offers fresh possibilities and markets that will be supplying high-value-added products and services. A new environment combining virtual reality (VR) and augmented reality (AR) to create a metaverse emerges at the intersection of cyber and physical interaction and data exchange (Park & Kim, 2022). A growing number of vital cyber-physical systems (CPSs), including the Industrial Internet of Things (IIoT) and industrial control systems (ICS), are anticipated to be managed using such a metaverse (Bitas, 2022; Park & Kim, 2022).

According to Bibri et al. (2022), "metaverse technologies have the potential to reduce the risk of disruption in businesses so that they are able to maintain their operations." This is especially true in the case of a pandemic, where a lack of labor is one of the most important factors that may negatively impact manufacturing operations (Belhadi et al., 2021; Bianco et al., 2023, p. 19). Many academics have faith that the metaverse (MV), with its many enabler technologies, including augmented reality, mixed reality, and virtual reality, could mitigate manufacturing disruptions (MFGDs) and call for research in this terrain (Bitas, 2022; Koohang et al., 2023; Steiner et al., 2023; Yao et al., 2022). In recent years, there has been progress in a few particular subfields of research. Moreover, earlier reviews offer fragmented qualitative and/or quantitative perspectives of specific disciplines (see Table 1). However, resilience is regarded as a particularly complex subject that necessitates all-encompassing viewpoints (Bianco et al., 2023; Kusiak, 2020).

Despite the growing interest of businesses in exploring the key role of metaverse and quality 4.0 technologies in achieving MFGRES, research has not given it the attention that it deserves. Academic literature is still missing a thorough examination of metaverse-enabled Q4.0 potential to reinforce MFGRES. To bridge this gap, the current study investigates the MV-based Q4.0 context systematically, focusing on the significant role of MV-based Q4.0 enabler technologies, MFGRES stages and MFGRES antecedents, which advance MFGRES. To do so, we carry out a systematic literature review (SLR), assessing the general role of metaverse-enabled Q4.0 in MFGRES, create a thorough metaverse enabled-Q4.0 MFGRES framework, and pay special attention to areas of application to deal with manufacturing issues caused by disruptions.

We carry out a systematic literature review (SLR), assess the general role of metaverse-enabled Q4.0 in MFGRES, create a thorough metaverse enabled Q4.0 MFGRES framework, and focus on areas of application to deal with manufacturing issues due to the pandemic.

Table 1. Eminent review studies on MV-enabled Q4.0 and MFGRES

Author/s	Method	TOS	Period	NA	Focus	Gaps
(Bianco et al., 2023)	Literature Review	Qualitative and quantitative	ND	ND	Industry 4.0 and manufacturing resilience	The study explored the role of Industry 4.0 in developing resilience for manufacturing companies. But there is no discussion on Quality 4.0-Metaverse nexus.
(Habibi Rad et al., 2021)	SLR & Bibliometrics	Qualitative and quantitative	2011 - 2021	144	Infrastructure resilience management and I4.0	The focus of the article was mainly on disaster risk management and infrastructure resilience
(B. Yang et al., 2022)	Literature Review	Qualitative	2018 - 2022	100	Metaverse in the field of fluid machinery pumps and fans	The focus was not on MV – Q4.0 nexus and manufacturing resilience
(Garavand & Aslani, 2022)	Literature Review	Qualitative	2006 - 2022	90	Metaverse and its impact on health	The article emphasizes the increasing interest in Metaverse. But it does not focus on the role of MV – Q4.0 nexus in manufacturing resilience.
(Mahmoodi et al., 2022)	SLR & Bibliometrics	Qualitative and quantitative	2004 - 2021	35	Impact of Industry 4.0 on bottleneck analysis in production and manufacturing	The only focus was identifying the research on I4.0 in production and manufacturing area.
(Adams, 2022)	Literature Review	Qualitative	ND	79	Virtual retail in the metaverse	The overall article was around the metaverse implementation, and

						the focus was not on manufacturing resilience.
	Literature Review	Qualitative	ND	ND	Significance of Quality 4.0 towards comprehensive enhancement in manufacturing sector	The study was much more generic and focused on the Quality 4.0 role in manufacturing sector.

Notes: This table shows some of the previous reviews on MV-based Q4.0 and MFGRES. It contains information about the study's authors, type of study (TOS), number of articles analyzed (NA), method, time frame, and main objective. Not defined periods/articles are referred to as ND.

The rest of the paper is organized as follows. We first introduce and use the SLR methodology in Section 2, construct the research questions (RQs), and evaluate the relevant studies. By introducing a metaverse-enabled Q4.0 MFGRES framework that encapsulates the links among metaverse-based Q4.0 enabler technologies, MFGRES antecedents, and MFGRES stages, we then respond to the RQs using the synthesized findings. As an added bonus, we use a COVID-19 application scenario in Section 3 to illustrate the usefulness and practicality of this framework. The implications of the study are explained in Section 4. Conclusions and suggestions for further research are provided at the end of the paper.

Appendix A provides the symbolic significance of the different abbreviations utilized throughout the paper.

2. Methodology

This study uses an evidence-based, systematic literature review method to address the known shortcomings of an expert review through the selection of ad hoc literature (Okoli & Schabram, 2010) or a narrative review (Tranfield et al., 2003). We use the five-step process from Denyer & Tranfield (2009), including a pilot search in the first step, to better understand the existing literature, create the selection criteria for the literature, and develop the research questions and subsequent steps. Therefore, the five steps of the systematic review used are shown in Fig. 1. The SLR methodology is also used separately in studies on quality 4.0 ((H.-C. Liu et al., 2023; Saihi et al., 2021), manufacturing resilience (Conz & Magnani, 2020; Shela et al., 2021), and the metaverse (Ritterbusch & Teichmann, 2023; Shen et al., 2021). Accordingly, this review summarizes the literature on the integration of the metaverse concept in quality 4.0 to achieve MFGRES.

2.1. Pilot search

As mentioned above, we carry out a pilot search as part of the first step to enhance our knowledge of the research field and existing body of literature. Moreover, requirements for the inclusion and exclusion of literature are also determined using the pilot search, in accordance with the guidelines provided by Denyer & Tranfield (2009). This is covered in detail in Section 2.3.

2.1.1. The research questions

A well-crafted, conclusive research question serves as the foundation for an appropriate SLR (Counsell, 1997). The most important and probably most challenging step in creating a research design is developing a research question. Once a research question has been developed, research strategies and methods can be chosen, meaning that research is built on the basis of sound research questions (Bryman, 2007). While the background information and context for the study are provided in the introduction section of a SLR paper, the introduction section is typically concentrated on introducing the topic, outlining any research gaps, and emphasizing the importance and relevance of the review. As has been done in similar studies (Núñez-Merino et al., 2020; Spieske & Birkel, 2021; Toorajipour et al., 2021), the methodology section is better suited for the research questions because they are more specific and directly related to the methodology. Furthermore, placing the research questions within the methodology section helps readers understand the purpose and scope of the study from the outset. The research questions are followed by a logical progression through the methodology, data analysis, and findings.

We come up with the research's main question after conducting a pilot search: How does MV-based Q4.0 contribute to MFGRES? This question was broken down into four subsequent sub-research questions (SRQs) in order to provide a clear response: To increase MFGRES, we first look for appropriate MV-based Q4.0 enabler technologies. As a result, we suggest SRQ1:

Which MV-based Q4.0 enabler technologies may support MFGRES?

Secondly, it is generally acknowledged in the literature that MFGRES is accomplished by mediating antecedents (Cotta & Salvador, 2020; M. Kumar et al., 2022). These are described as factors by Pal et al. (2014) that "improve the capacity of a business to rapidly and effectively recuperate from a disruptive event." Therefore, we think that enabler technologies reinforce particular antecedents rather than directly affect MFGRES. Therefore, identifying these antecedents is crucial when examining MV-based Q4.0 purpose within MFGRES. As a result, we create SRQ2:

Which MFGRES antecedents benefit from MV-based Q4.0 applications?

Thirdly, as noted by other researchers (Ismail et al., 2011; J. Yang et al., 2022), MFGRES can be developed in five stages before and after a manufacturing disruption: readying, protection, response, recovery, and adaptation. To enable a targeted use of MV-based Q4.0, it is crucial to comprehend which stages MV-based Q4.0 enable MFGRES antecedent's role. On the basis of this, we propose SRQ3:

Which MFGRES stages do the MV-based Q4.0 applications enhanced MFGRES antecedents support?

Fourthly, according to academics, the metaverse is anticipated to have the ability to reduce manufacturing risks brought on by disruptive events (Lee & Kundu, 2022). To improve MFGRES during a pandemic, the literature has yet to include contributions that comprehensively describe the application areas for MV-based Q4.0 enabler technologies. As a result, we expand on the previous SRQs to respond to SRQ4:

How can MV-based Q4.0 applications enhance MFGRES during a pandemic?

2.2. Identifying studies

A database-driven search is used in the second stage of this study to locate the necessary publications since an SLR should embrace all relevant literature to answer the research question (Denyer & Tranfield, 2009). Selecting the database that houses the input data is typically the first step. Our sources come from the Scopus database, which has previously been deemed trustworthy by authors such as Kipper et al. (2020), Meyers et al. (2021) and Oliveira et al. (2018). The largest database of scientific peer-reviewed literature, Scopus, created by Elsevier BV Company, USA, contains more than 22,000 titles and high-impact scientific research from worldwide publishers (Elsevier.Com). It is selected for this study because it has consistent document repositories and additional features such as the country of each author, citations for each paper, and other data that is both quantitatively and qualitatively important for the study.

We have to choose the proper search terms before querying the database. For the purpose of locating relevant articles in the given database, we develop 31 keywords during brainstorming sessions using basic literature. Three topics that are pertinent to this paper are covered by the keywords: manufacturing (seven keywords), resilience (six keywords), and Quality 4.0-Metaverse nexus (18 keywords). The titles, abstracts, and keywords of the articles are combined with one keyword from each topic. The words "risk," "agility," and "disruption" add the resilience angle this paper needs. The Quality 4.0-Metaverse nexus perspective is subsequently included. This category is founded on the terms "metaverse" and "quality 4.0". The additional keywords "Virtual reality," "Augmented reality," "Extended reality," "blockchain," "Artificial intelligence," "data analytics," "internet of things," "cyber-physical," and "machine learning" are taken from current research that examines MV-based Q4.0 primary technological catalysts in the context of MFGRES

(Bordegoni & Ferrise, 2023; Choi et al., 2022; Yao et al., 2022). Moreover, this review does not have a time limit because applying metaverse techniques to manufacturing is still a relatively new idea. As shown in Table 2, with the help of the given keywords and Boolean connectors, a search string is made.

Table 2. Scopus database research protocol

<table>
<tr><td rowspan="5">Search String</td><td>Cluster 1: Resilience</td><td>“Risk” OR “Resilience” OR “Agility” OR “Flexibility” OR “Robust*” “Disruption”</td></tr>
<tr><td colspan="2">AND</td></tr>
<tr><td>Cluster 3: Manufacturing</td><td>“Manufacturing” OR “Assembly” OR “Production” OR “Operations” OR “Quality” OR “Lean manufacturing” OR “Maintenance” OR “Process”</td></tr>
<tr><td colspan="2">AND</td></tr>
<tr><td>Cluster 2: Quality 4.0-Metaverse nexus</td><td>“Virtual reality” OR “Metaverse” OR “Augmented reality” OR “Extended reality” OR “Blockchain” OR “Quality 4.0” OR “Internet of things” OR “Machine learning” OR “Artificial intelligence” OR “Predictive analytics” OR “Automated quality*” OR “Cyber-physical system” OR “Cloud computing” OR “Deep learning” OR “3D*” OR “Digital*” OR “Simulation” OR “Human-machine interface”</td></tr>
</table>

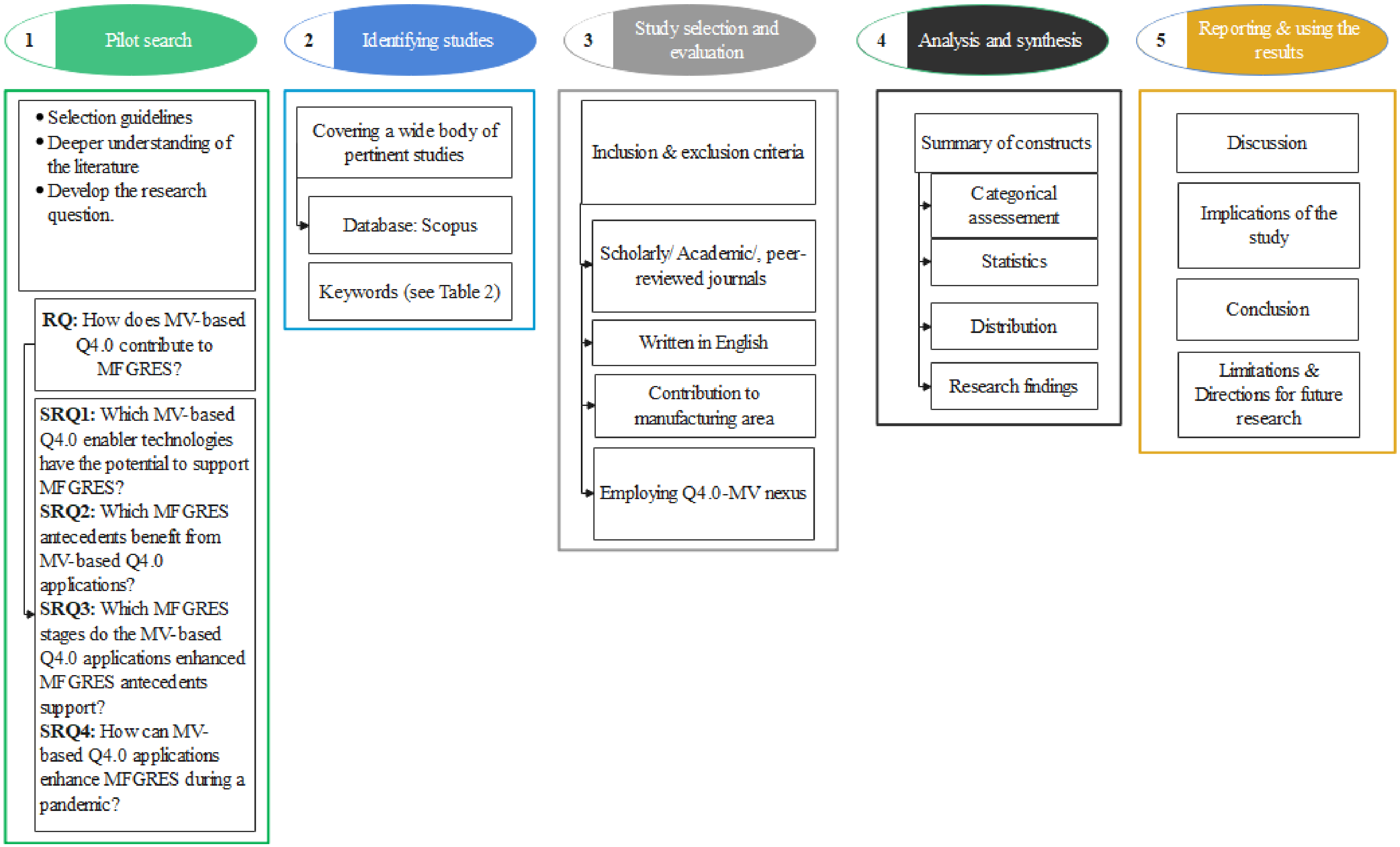

Fig. 1. Research process for conducting the study, adapted from Denyer & Tranfield (2009)

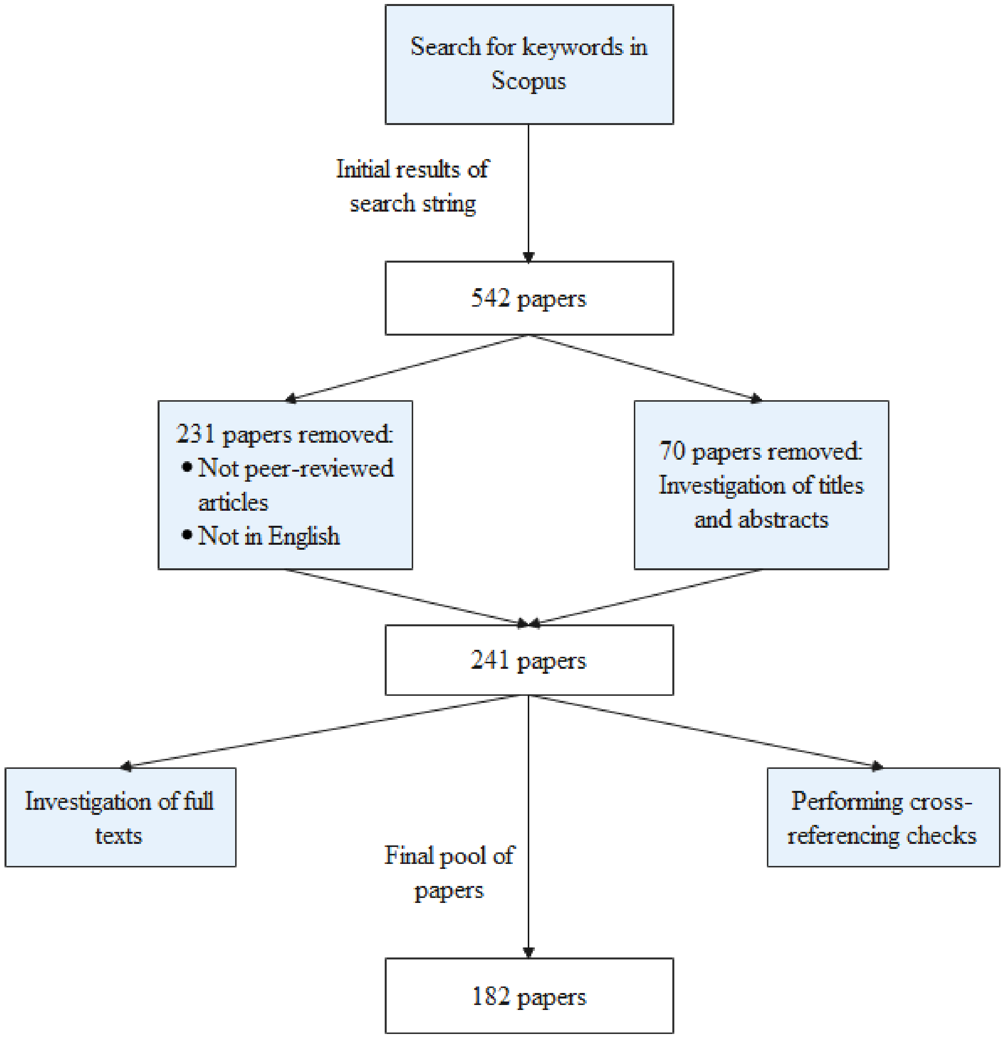

Fig. 2. Process used for the articles selected for this study

2.3. Study selection and evaluation

The selection and evaluation of studies is the third step in an SLR. The previously discovered articles are evaluated using a set of criteria, and if they do not meet the criteria or are of low scientific reliability, they are disqualified from the research (Denyer & Tranfield, 2009). The Scopus database returned 542 studies after the keywords are applied. We concentrate on articles that appear in English language, peer-reviewed academic journals to ensure the validity of the data (Okoli & Schabram, 2010). Further limiting the selection to reputable scientific journals, the 2018 ABS and VHB ratings are used to exclude conference proceedings, books, trade publications, magazines, and newspapers. This brings the total down to 241 publications. The MV-based Q4.0 solutions that support MFGRES are the main focus of the reading of the titles, abstracts, keywords, and conclusions. Contributions that describe the relationship between at least one MV-based Q4.0 enabler technology and one MFGRES antecedent are given special consideration. Then, 59 studies are dropped. A final sample of 182 pertinent, excellent papers serve as the foundation for the analyses that follow. Fig. 2 depicts the selection and evaluation process for the studies.

2.4. Analysis and synthesis

To gain new perspectives, we meticulously examine the selected literature (Denyer & Tranfield, 2009), initially concentrating on each paper separately. We look at five factors with the goal of learning more about the research sample focusing on the intersections of MFGRES and MV-based Q4.0: the publication year, the publication location (both in Section 2.5.1), the MV-based Q4.0 technologies examined (Section 2.5.2), the leveraged MFGRES antecedents (Section 2.5.3), as well as the MFGRES stages (Section 2.5.4). The relationships among MV-based Q4.0 technologies, MFGRES antecedents, and MFGRES stages are then revealed by integrating the individual papers and suggesting a holistic MV-based Q4.0 MFGRES framework (Section 2.5.5).

2.5. Reporting and using the results

The findings of this study, which are intended for an academic audience, are presented as statistics, tabulations, and discussions, in accordance with the recommendations of Denyer & Tranfield (2009). An overview of the literature reviewed and the data that is extracted is provided in the results and discussion section. highlighting what was previously known and what was unknown regarding the research questions.

2.5.1. Distribution of studies

Regarding the publication year, the first pertinent contribution is made in 2012. The sample after that shows a steady rise in the body of literature linking MFGRES and MV-based Q4.0. The mean annual citations of the articles published between 2012 and 2023 are shown in Fig. 3 along with the growth in publications each year. Of note, 2022 has produced the most publications (50), followed by 2021 (38). Over two-thirds of the papers found are published after 2020, which is consistent with recently made contributions that highlight the metaverse's expanding significance in MFGRES (Bordegoni & Ferrise, 2023; Choi et al., 2022; Yao et al., 2022). This development is due to two factors. Firstly, over the past few years, manufacturing disruptions (MFGDs) have become more severe, including those caused by natural catastrophes, the US-China trade conflict, Brexit, and the COVID-19 epidemic. This motivates research and business to develop new manufacturing risk management (MFGRM) strategies. Secondly, as metaverse technologies become more developed and applicable (Park & Kim, 2022), it may be possible to find ways to improve MFGRES and mitigate recurrent, serious MFGDs. We are certain that research in this area will pick up speed even more over the coming few years as a result of the COVID-19 pandemic.

As stated in Section 2.3, in order to guarantee the integrity of the data, we mainly focus on peer-reviewed articles from journals with an VHB or ABS rating. In total, 136 different journals published 182 papers. Most of the studies in this field are found in “Computers & Industrial Engineering”, which has seven publications. “IEEE Access” and “the International Journal of Production Research” each have five publications in this field. Of note, the majority of publications deal with production, logistics, and operations journals. However, recent developments in this area are also presented in journals that are devoted to information and communication technologies as well as general management. This is clear from the fact that only one article is published in each of the 113 journals. This highlights the interdisciplinary nature of the subject. Table 3 displays the number of articles that appear in various journals between 2012 and 2023.

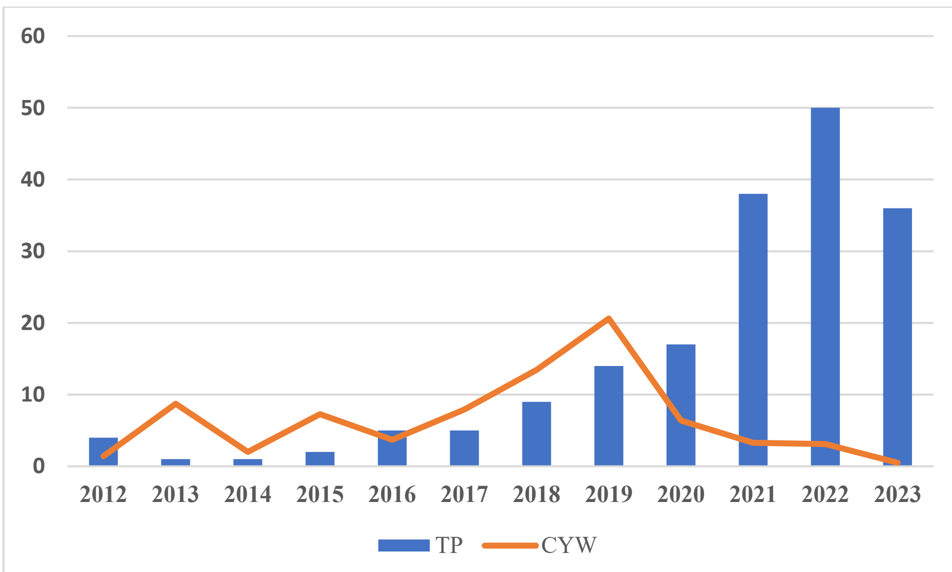

Fig. 3. Trend in MV-based Q4.0 and MFGRES research (as of June 2023)

Notes: This figure shows the annual trend in the publications on MV-based Q4.0 and MFGRES, its popularity and influence between 2012 and 2023. Here, TP = total publication, and CYW = mean citations year-wise.

Table 3. Distribution of studies journal-wise.

Journal Name	**No. of articles**
Journals Having Single Paper	113
Computers and Industrial Engineering	7
IEEE Access	5

International Journal of Production Research	5
International Journal of Production Economics	4
Nuclear Fusion	4
Reliability Engineering and System Safety	4
Sustainability (Switzerland)	4
Transportation Research Part E: Logistics and Transportation Review	4
Engineering Applications of Artificial Intelligence	3
IEEE Transactions on Engineering Management	3
Annals of Operations Research	2
Computers in Industry	2
Expert Systems with Applications	2
Future Generation Computer Systems	2
IEEE Internet of Things Journal	2
International Journal of Advanced Manufacturing Technology	2
International Journal of Communication Systems	2
International Journal of Logistics Management	2
Journal of Engineering, Design and Technology	2
Journal of Manufacturing Systems	2
Logistics	2
Operations Management Research	2
Sustainable Cities and Society	2

2.5.2. Metaverse based Quality 4.0 enabler applications

Technologies such as distributed ledgers, artificial intelligence, and augmented reality become crucial enablers as the global industrial complex moves toward realizing the principles of I4.0 and beyond. Throughout the past ten years, the metaverse as an innovative notion has established itself as one of the most important enablers for technological and digital advancement in a variety of engineering fields (Park & Kim, 2022). In order to uncover a fully digitalized world with comparable properties to the real world, the metaverse has the potential to bring together components from collaborative computing platforms as well as the digital transformation of physical systems, and cutting-edge learning systems (Lee & Kundu, 2022).

Quality 4.0 encompasses a broad range of technologies that present a promising environment for metaverse applications. A previously unexplored metaverse offers fresh possibilities and markets that will be supplying high-value-added goods and services. The collection, aggregation, and exchange of data are all undergoing rapid change as a result of the digital transformation of vital infrastructures, including those in the fields of advanced manufacturing, transportation, energy, and life sciences (Yao et al., 2022).

The characteristics of the metaverse prevent there from being a single definition and its potential applications in MFGRES literature vary between researchers and studies (Park & Kim, 2022). Furthermore, " Technologies related to the metaverse are still lacking" (Ning et al., 2023). Therefore, a comprehensive and mutually exclusive classification is still lacking. In order to write this paper, we look over recent classifications in the MFGRES field. Some studies focus on virtual reality and mixed reality and limit the use of the metaverse to gaming and entertainment purposes (Kerdvibulvech, 2022; D. Shin, 2022). Other researchers (Lee & Kundu, 2022; Lin et al., 2022; Yao et al., 2022) adopt a more comprehensive approach and include a variety of cutting-edge technologies throughout the entire manufacturing area. For this study, we adopt the latter strategy, which helps us to achieve our goal of offering a comprehensive view of MV-based Q4.0 use throughout the manufacturing process to improve MFGRES. The virtual MFG technology portfolio identified by Di Pasquale et al. (2022) serves as our starting point. They develop a framework with eight technologies based on a review of the literature on virtual MFG papers: blockchain (BC), augmented reality (AR), virtual reality (VR), mixed reality (MR), AI, big data analytics (BDA), cloud computing (CC), and the internet of everything (IoE). As an extension, we take into account digital twins (DT), as many academics claim that this technology certainly belongs to the metaverse (Bordegoni & Ferrise, 2023; Park & Kim, 2022). Other popular agile technologies covered in the metaverse context, such as 3D modeling, haptics, robotics, and avatars, can be classified into at least one of the nine categories without sacrificing information. We briefly describe each of the nine MV-based Q4.0 enabler technologies before determining which one is most relevant. With this in mind, Table 4 is created to link the relationship between Q4.0 features and nine metaverse technologies that can be used to enhance MFGRES.

BC (A) is a distributed and decentralized digital ledger technology that permits the safe and transparent storing of data and transactions among numerous participants or nodes (Lin et al., 2022). It offers a method of securely storing and verifying data in an unchangeable way. A blockchain is fundamentally a continually expanding list of records, or blocks, that are connected by means of cryptographic techniques (Almasoud et al., 2020). Each block includes a collection of transactions or data as well as a special code known as a hash. A chain-like structure is produced by the hashing of each block, which is created based on the data it includes and the hash of the previous block (Lin et al., 2022). The immutability and integrity of the data stored on the BC are guaranteed by this connection (Borowski, 2021). In the context of manufacturing, BC can be used to assist manufacturers in enhancing quality control procedures. Manufacturers can guarantee adherence to rules and industry standards by capturing quality-related data, monitoring, and credentials on the BC (Borowski, 2021; Lin et al., 2022). As a result of BC's transparent, decentralized, and tamper-resistant characteristics, MFGRES can greatly profit from these application areas by constructing resilient structures and procedures that can endure and recover from disruptions more efficiently (Banerjee, 2019).

Table 4. Quality 4.0- Metaverse nexus in MFGRES.

	Quality 4.0 features								
Metaverse Techniques	Automation of Inspection	Integration	Customer Centeredness	Supplier Collaboration and Traceability	Real-time Monitoring and Control	Connected Systems	Continuous Improvement and Feedback Loops	Visualization and Decision Support	Proactive Quality Management
A Blockchain		X	X	X	X	X			
B Augmented reality	X			X	X		X	X	X
C Virtual reality		X		X	X		X	X	X
D Mixed reality	X	X			X	X		X	
F Artificial intelligence	X	X	X	X	X	X	X	X	X
F Big data analytics					X	X	X	X	X
G Digital twins	X	X			X	X	X	X	X
H Cloud computing	X	X	X	X		X	X		
I Internet of everything	X	X	X	X	X	X		X	

Element ID

AR (B) refers to a technology that enhances a user's perception of and interaction with the physical world by superimposing computer-generated digital content, such as pictures, videos, or 3D models, over the real-world environment (Di Pasquale et al., 2022). AR creates an interactive and immersive experience by fusing elements of the virtual and real worlds in real-time (Künz et al., 2022). As a result, AR enables manufacturers to see and interact with digital 3D models of their goods or parts in a physical environment. Furthermore, AR has enormous potential for enhancing productivity, efficiency, and safety in the manufacturing sector (Morimoto et al., 2022). By giving workers access to real-time visual information, guidance, and support, AR improves worker capabilities, lowers errors, and streamlines various manufacturing processes, ultimately producing better results and increasing customer satisfaction (Zigart & Schlund, 2020). For MFGRES, AR offers training, real-time support, and the ability to solve problems. AR also encourages flexibility, enhances decision-making, and guarantees continuity in the face of challenges or disruptions (Masood & Egger, 2020; Wang & Dunston, 2006).

VR (C) is a term for a type of technology that submerges users in a computer-generated, simulated environment that can be felt through touch, hearing, and sometimes visual perceptions (Adams, 2022). VR immerses users in an entirely artificial or digitally recreated environment in an effort to foster a sense of presence and engagement (Berg & Vance, 2017). To provide an immersive experience, VR typically combines hardware and software components. This includes putting on a Head-Mounted Display (HMD) or VR headset, which usually has motion tracking sensors, built-in displays, and audio output (Dincelli & Yayla, 2022). To develop simulations or virtual replicas of production lines, manufacturing facilities, or processes, VR and digital twin technology can be combined (Künz et al., 2022). Prior to physical production, MFGRES can use VR to visualize and assess product designs. As a result, design flaws are found, ergonomics are improved, and product functionality is enhanced (Sadhu et al., 2023). VR equips manufacturers to adapt to disruptions, mitigate risks, and maintain business continuity by enabling virtual training, remote collaboration, remote maintenance, digital twin simulations, and process optimization (Berg & Vance, 2017).

MR (D) refers to a technology that combines aspects of both VR and AR to produce an interactive and seamless fusion of the real and the digital worlds (Morimoto et al., 2022). It entails the real-time integration of virtual information and objects into the physical environment, enabling users to interact with both digital and physical components at the same time (Naticchia et al., 2020). Users can perceive and communicate with virtual objects in MR experiences as though they were a real part of the environment because they are aligned and anchored with the physical surroundings (Farshid et al., 2018). This is accomplished by using specialized equipment, such as glasses or headsets, which can superimpose virtual content over the user's perception of the outside world. A variety of functionalities and interactions, such as object recognition, spatial mapping, motion tracking, and recognizing gestures can be provided by MR (Farshid et al., 2018). With the help of these MR applications, virtual objects can communicate with actual surfaces, react to user behaviors, and keep a sense of realism and presence (Maas & Hughes, 2020). MFGRES uses MR to facilitate remote team collaboration among geographically separated teams during the manufacturing process (Vasarainen et al., 2021). Using MR devices, workers can communicate virtually in a shared MR environment, interact with virtual 3D models, and discuss designs or production issues (Steiner et al., 2023). As a result, manufacturers can iterate designs more quickly, optimize the functionality of their products, and boost their resilience by spotting and fixing problems early in the development process (Bottani et al., 2021).

AI (E) is a catch-all term for techniques that help systems make adaptive decisions using large, potentially unstructured data sets (Acerbi et al., 2021; Ahmed et al., 2023). Key applications in this area include cognitive computing, machine learning, natural language processing (NLP), robotics, computer vision, and expert systems (Bag et al., 2023; Cravero & Sepúlveda, 2021). The relationship between AI and BDA is still hazy. According to some researchers, BDA and AI are mutually inclusive (Allam & Dhunny, 2019; Bag et al., 2021). Despite the fact that big data can serve as an input for AI (Misra et al., 2022), we choose to treat the two technologies independently, as other researchers have done (Özdemir & Hekim, 2018a; Pramanik et al., 2018). While BDA research is still in its early stages, AI has received considerable attention in MFGRES papers and is being used by businesses progressively (Acerbi et al., 2021; Chen et al., 2022). As a result, we make an effort to differentiate between research on traditional BDA (focused on extracting knowledge from big data) and research on AI-based future-proofing (focused on decision-making and self-learning). Any AI method used in MFGRES is deemed artificially intelligent if it can choose an appropriate course of action on its own and achieve success in an unexplored MFG environment (Sharma et al., 2022).

BDA (F) is the synthesis of methods, equipment, and procedures for turning unstructured, semi-structured, and structured data from various sources into information that can be used as a basis for making decisions (Bag et al., 2023; Cravero & Sepúlveda, 2021). The crucial phases of BDA are collecting information, data management, storage, and processing, as well as data analysis, visualization, and reporting. Because BDA supports MFGRES, as has been empirically demonstrated by researchers (Ma et al., 2022; Majeed et al., 2021), this technology is seen as a crucial component of upcoming agile MFGRES initiatives. For instance, BDA enables businesses to gather and analyze sizable amounts of data from sensors and IoT devices integrated into manufacturing machinery (El Jaouhari et al., 2023; Papadopoulos et al., 2022). Manufacturers may detect anomalies, foresee maintenance needs, and prevent equipment failures by constantly tracking equipment performance and analyzing data in real-time (Ma et al., 2022). This promotes equipment resilience, reduces expensive downtime, and guarantees continuous production. BDA also aids in spotting trends, patterns, and potential quality problems (Misra et al., 2022). Moreover, manufacturers can perform real-time quality control regulations, recognize deviations, and act quickly to correct them by analyzing data from sensors, inspections, and other sources (Bag et al., 2021). This increases the robustness of manufacturing processes, lowers defects, minimizes rework, and improves product quality (Özdemir & Hekim, 2018a).

DT (G) refers to a virtual representation or replica of a physical object, process, or system (Ma et al., 2022). It is a digital equivalent that mimics the functionality, personality traits, and actions of its physical counterpart in real-time. Data from IoT devices sensors and other sources is combined to create DTs; these record and model the physical item or system (Bordegoni & Ferrise, 2023; El Jaouhari, Azari, et al., 2022). A DT is more than just a straightforward 3D model. In manufacturing, DTs can stand in for specific products, entire manufacturing processes, or a whole factory (Tao et al., 2019; Zhu et al., 2019). They give manufacturers the ability to simulate scenarios, forecast breakdowns in equipment, and analyze performance in real time (Tao et al., 2019). DTs can help with upkeep, quality assurance, and predictive analytics, which will ultimately boost productivity, decrease downtime, and increase resilience in manufacturing operations (Ma et al., 2022). By leveraging DTs, businesses can gain a deeper knowledge regarding their physical assets, processes, and systems, leading to enhanced decision-making, operational efficiency, and overall resilience (Zhu et al., 2019).

CC (H) refers to the transmission of computing assets, such as storage, servers, networking, databases, software, and other services, over the internet (Afzal & Kavitha, 2019). rather than relying on local equipment or infrastructure. It enables users to access and use these resources whenever they need them from distant servers (P. Kumar & Kumar, 2019). Different combinations of cloud, fog, and edge computing are possible depending on the needs of a given application and the design of the system (S. Shin et al., 2021). For instance, edge computing can be used to locally process data gathered from IoT devices at the edge before sending a subset of that processed data to the cloud for further processing and long-term archiving (Cao et al., 2020). In order to balance the trade-offs between localized processing and centralized cloud resources at the edge, a distributed and scalable computing system is made possible by this hierarchical approach (Kochovski et al., 2020). The decentralized nature of the CC makes it possible for straightforward gathering of data, storage, processing, and exchange among numerous entities. This enhances data management both within and between businesses (Banfi et al., 2022). Manufacturers can scale their computing resources up or down for MFGRES based on demand. Moreover, reliable data backup, as well as recovery systems, are often supplied by CC providers (S. Shin et al., 2021). Manufacturers can store their vital information and software in the cloud, protecting it from loss or disruption and ensuring that it can be recovered (Sebbar et al., 2022). The efficacy of CC in enhancing MFG performance is empirically demonstrated. In the automotive sector, for instance, according to J. -L. Liu et al. (2019), SMEs using the cloud are more resilient compared to their non-cloud rivals.

IoE (I) is the notion of linking not only individuals and gadgets but also common machines, objects, and systems to the internet so they are able to interact with one another (Miraz et al., 2015). It broadens the definition of the IoT to encompass not only tangible gadgets but also unusually connected things like infrastructure appliances, and even abstract things like processes, data, and services (Shilpa et al., 2019). In the IoE, systems and items have connectivity, actuators, and sensors that enable them to gather and exchange information, receive commands, and automate procedures (DeNardis, 2020). This ecosystem's interconnectedness allows for easy communication, data exchange, and cooperation among its various components, opening up new possibilities and promoting innovation across numerous industries (Shilpa et al., 2019). For MFGRES, the IoE enables the implementation of smart manufacturing principles, such as the Industrial Internet of Things (IIoT), where systems, machines, and processes are connected (Abdel-Basset & Imran, 2020). Manufacturers are able to obtain real-time insights into manufacturing quality and efficiency through the integration of data from various sources, including sensors, production lines, and quality control systems (DeNardis, 2020). With the help of this data-driven technique, processes can be continuously improved, problems can be identified early, and resource allocation can be optimized, increasing resilience and productivity (Pelton & Singh, 2019). Furthermore, IoE generates a vast amount of data from various sources inside the manufacturing environment (Shilpa et al., 2019). Manufacturers can gain useful insights into their operations, spot patterns, streamline procedures, and come to good decisions by utilizing this data and advanced analytics, leading to overall resilience in the face of market fluctuations or disruptions (DeNardis, 2020; Shilpa et al., 2019).

Firstly, we start by counting all the technology references in our sample in order to determine which MV-based Q4.0 enabler technologies are the most current. Secondly, in relation to the overall number of references, we identify the relative proportion of enabler technology references using a method as presented by Ramirez-Peña et al. (2020). Multiple enabler technologies are discussed in some publications, yielding 345 enabler technology references from 182 articles. Fig. 4 shows the outcomes.

Since AI is regarded as fully-developed in research and business (Acerbi et al., 2021; Ahmed et al., 2023), it is not surprising that the majority of papers identified discuss AI solutions. The number of contributions is low for all other enabler technologies. This result is unforeseen given that many academics believe the metaverse will significantly improve MFGRES (Lee & Kundu, 2022; Lin et al., 2022; Steiner et al., 2023). This ultimately results in the conclusion that the aspiring and particular application domains of each MV-based Q4.0 enabler technology in MFGRES have not yet been fully explored by research. Moreover, we analyze the papers presenting more than one MV-based Q4.0 enabling technology, finding 75 participations. In several instances, they are the subject of separate scholarly discussions. Therefore, the potential benefits of combining different enabler technologies have largely been ignored up until now. The exceptions are Gellers (2021), who discuss the use of VR in AI, and Parker & Bach (2020), who propose the idea of a "business capacity assessment approach and sharing system" that uses BC, AI, and the IoT to choose the best suppliers.

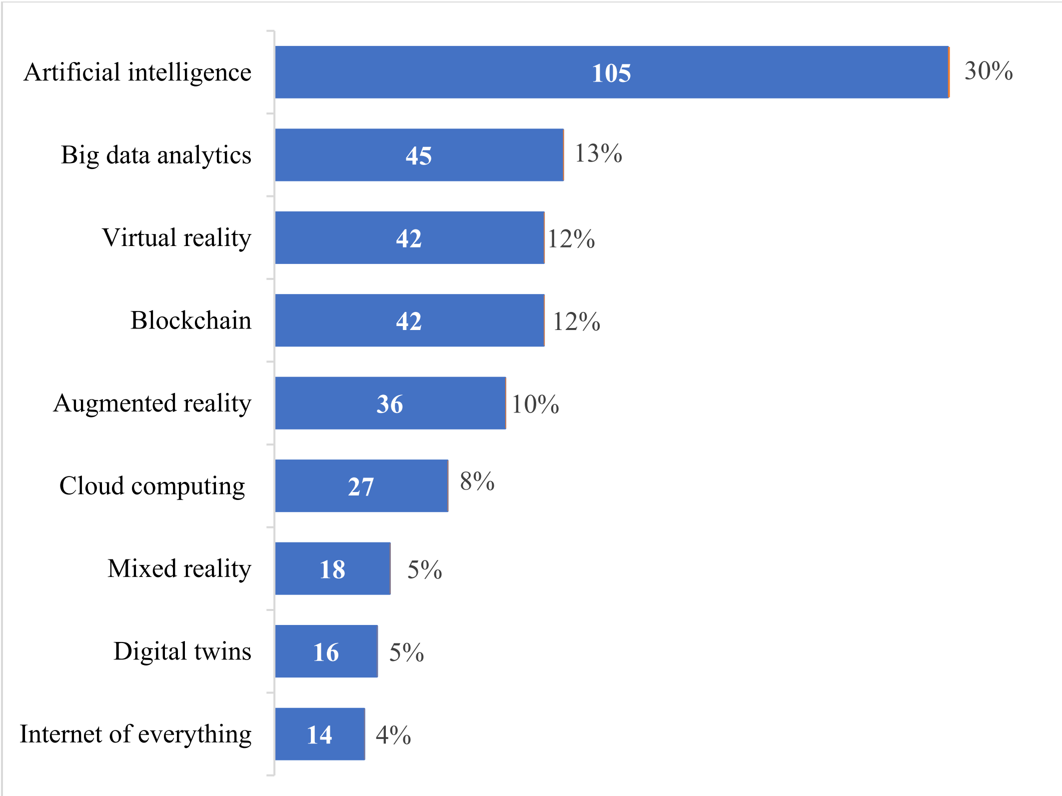

Fig. 4. Aggregate value and relative proportion of MV-based Q4.0 MFGRES enabler technology references

2.5.3. Manufacturing resilience antecedents

We assert in Section 2.1 that MV-based Q4.0 applications do not immediately have a role in achieving MFGRES; rather, particular antecedents are necessary as mediating factors. We expand on the work of Touriki et al. (2021). The MFGRES framework identifies manufacturing (re-)configuration capabilities, agility, communication, and a supporting MFGRM culture as key enablers for differentiating MFGRES antecedents. Numerous academics, with some variation, have supported this central idea (Dwaikat et al., 2022; Hosseini et al., 2016; Longo et al., 2022; Sheth & Kusiak, 2022). We find that the majority of the articles in our sample identify techniques to improve agility (~67%) and (re-)configuration capacities (~43%). We choose to further segment them in order to better comprehend the connection between MV-based Q4.0 applications and these two antecedents. While agility is typically thought of as a combined element that includes flexibility and transparency (Dutta et al., 2022; Iranmanesh et al., 2023), manufacturing (re-)configuration has four different perspectives - adopting the continuous improvement concept, building redundancy into manufacturing operations, empowering knowledge, and planning and managing the entire manufacturing system (Hashemi-Petroodi et al., 2021; Lepuschitz et al., 2011;

Wan et al., 2018). The level of analysis for this study and the MFGRES antecedents are shown in Fig. 5.

This subsection provides a brief overview of all the MFGRES antecedents discussed in this paper before thoroughly evaluating our sample. The level of visibility, openness, and accessibility of data, workflows, and other operations within a manufacturing company or its supply chain is referred to as transparency (s) (Iranmanesh et al., 2023). It entails the timely and clear dissemination of information to all pertinent stakeholders at every level to promote collaboration, trust, and accountability (Bai & Sarkis, 2020).

Flexibility (t) refers to a manufacturing system's or organization's capacity to swiftly and successfully respond to shifts in demand, product specifications, marketplace dynamics, and additional factors (Hou, 2020). It requires the ability to rapidly alter operations, assets, and production methods without compromising effectiveness or quality (Delic & Eyers, 2020; Umam & Sommanawat, 2019).

Communication (u) in the context of MFGRES refers to the sharing of knowledge, concepts, directives, and suggestions among various individuals, groups, departments, and parties involved in the manufacturing process (Kurfess et al., 2020). It entails the efficient sending and receiving of messages in order to guarantee precise comprehension, coordination, and cooperation throughout manufacturing operations (Villalba-Diez & Ordieres-Meré, 2015). The importance of communication is highlighted in the context of MV-based Q4.0 because "a business cannot reap the full benefits from innovative technologies if its other manufacturing stakeholders remain miscommunicating" (Lee & Kundu, 2022).

Empowering knowledge (v) in an MFGRES context entails setting up an environment and putting strategies in place that promote knowledge acquisition, sharing, and consumption across the organization (Carayannis et al., 2018). Creating a culture of knowledge sharing, supporting ongoing learning, and promoting cross-functional collaboration are some examples of knowledge-fostering strategies (Hodorog et al., 2021). When dealing with MFGDs, having such types of tools is essential to enable scenario simulations and vulnerability analyses (Cillo et al., 2021; Hodorog et al., 2021).

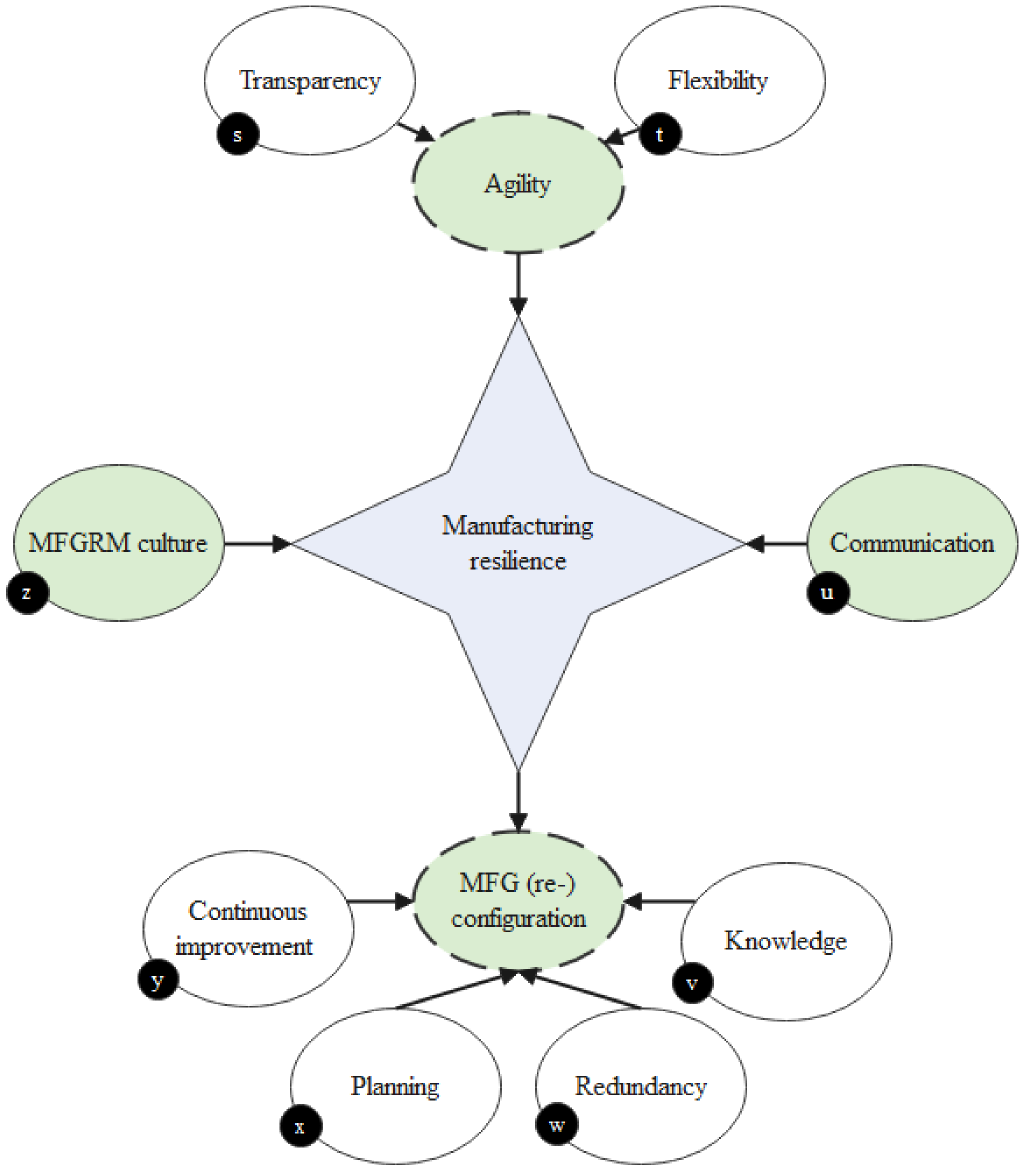

Fig. 5. MFGRES antecedents

Redundancy (w) refers to having backup or duplicate processes, systems, components, or resources in place to guarantee continuity and lessen the effects of breakdowns, disruptions, or unanticipated occurrences (Beer, 2018). Redundancy strategies have a price, even though they are thought to be useful for overcoming disruptions (Emami-Mehrgani et al., 2011), so they must be used carefully. Multiple sourcing, increased inventory, and backup capacity in manufacturing as well as transportation are the three most eminent measures (Malhan et al., 2019).

Planning (x) encompasses coordinating and scheduling production tasks to guarantee the dependable operation of manufacturing facilities and equipment (J.-L. Liu et al., 2019). Moreover, planning enables businesses to proactively recognize and tackle potential risks, reducing disruptions and strengthening the capacity to react to unexpected occurrences (Allaoui et al., 2019). Decision-makers in an MV-based Q4.0 environment must be able to analyze vast amounts of data and derive insightful conclusions. With the help of these insights, production planning can be made more effective by spotting patterns, anticipating changes in demand, and locating areas for process enhancement (Lee & Kundu, 2022).

Continuous improvement (y) in the context of MFGRES entails continuously assessing and optimizing systems, processes and approaches to better anticipate and react to disruptions, potential risks, and shifting market conditions (McLean et al., 2017). Risk identification and alleviation, measurement and monitoring, and staff empowerment are a few instances of continuous improvement techniques (Khan et al., 2019). Working together with suppliers, customers, and industry professionals can in such a scenario offer helpful insights that support efforts for continuous improvement (McLean et al., 2017).

Building a manufacturing risk management culture (z) has a very diverse set of antecedents, such as clear responsibilities and roles, risk awareness and education, and leadership commitment (S. Kumar & Anbanandam, 2020). Decision-makers in an MV-based Q4.0 environment must be able to use real-time data, sophisticated analytics, simulation tools, and improved communication to develop a proactive, data-driven risk management strategy that ensures worker safety, business continuity, and asset protection (Koohang et al., 2023; Queiroz et al., 2023).

To determine which MFGRES antecedents in our sample are the most relevant, we use the same reasoning as in Section 2.5.2. Following Ramirez-Peña et al. (2020), we determine the aggregate number and relative proportion of MFGRES antecedents covered. Numerous topics are covered in most publications, leading to 365 MFGRES antecedent references from 182 articles. Fig. 6 presents the complete findings.

The research centers on (re-)configuration and agility elements, with flexibility and transparency leading the way. This result makes sense because, according to Lin et al. (2022), MV-based Q4.0 enabler applications in manufacturing are primarily thought of as decision-support tools for handling major disruptions. Since this MFGRES antecedent is referred to as "the glue that maintains businesses jointly" in times of crisis, the restricted implementation. of communication is somewhat remarkable (Kurfess et al., 2020). To clarify this finding, we refer to Ayisi Nyarko & Kozári (2021), who claim that traditional information and communication technologies have significantly benefited communication. Therefore, we think that MV-based Q4.0 concentrates on other undeveloped elements. creating a culture of MFGRM and exploring whether MV-based Q4.0 could even serve as a resilience reducer for this component (Yao et al., 2022), or also performs a supporting role.

Furthermore, we discover two separate research strings. Knowledge and planning are typically discussed independently of other elements. The reason, in our opinion, is that manufacturing and SCM research have historically been kept apart. We are confident that combining the results from both research strands and taking into account the flexibility, transparency, and communication elements directly from MV-based Q4.0 supported manufacturing development, including supplier selection and network design, can result in long-lasting improvements in these MFGRES antecedents.

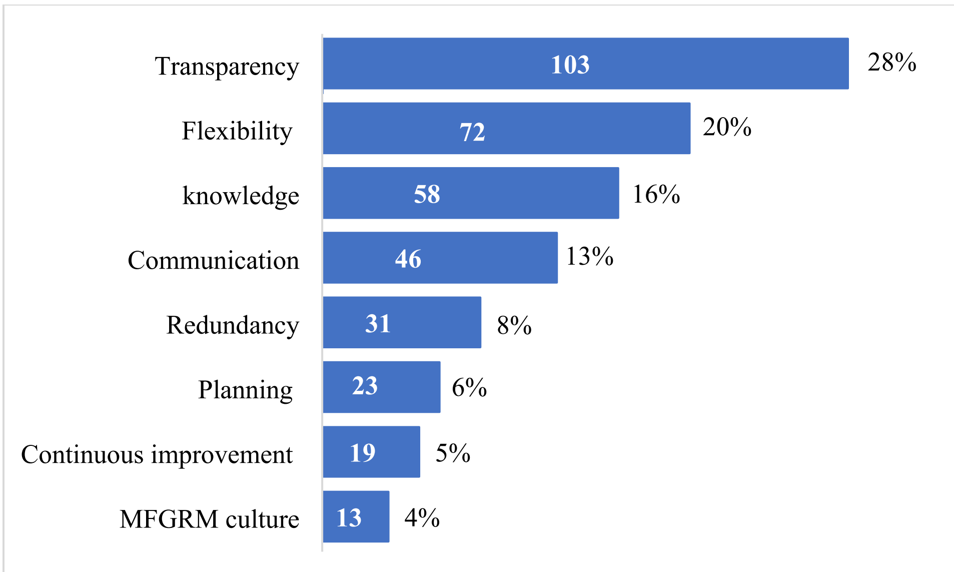

Fig. 6. Aggregate value and relative proportion of MFGRES antecedent references

2.5.4. Manufacturing resilience stages

As a final point, this section discusses MFGRES stages before introducing our MV-based Q4.0 MFGRES framework. The research of Kusiak (2020), who identified five distinct stages - readying, protection, response, recovery, and adaptation - is the foundation for this section. These stages are outlined in chronological order in Fig. 7.

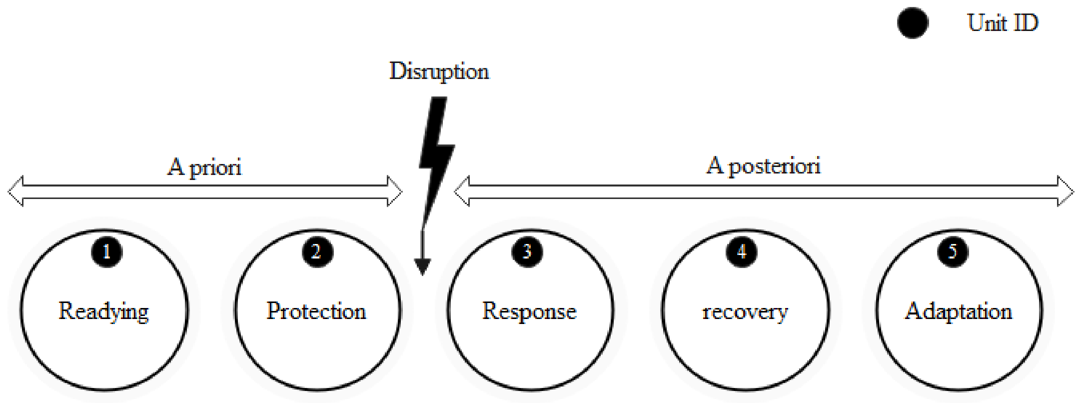

Fig. 7. MFGRES stages

Readying (1) entails taking proactive steps to get ready for potential disruptions (Rajnai & Kocsis, 2018). It includes risk analysis, emergency planning, and the establishment of systems and procedures to mitigate the likelihood of manufacturing disruptions and to decrease their negative effects (Schumacher et al., 2016). The purpose of protection (2) measures is to mitigate the likelihood and impact of disruptions (Petrović & Kankaraš, 2018). When a disruption happens, the response (3) stage concentrates on quick actions that reduce the effect and restore operations (Belhadi et al., 2021). After dealing with the immediate impact, the recovery (4) stage seeks to resume regular operations and make up for any losses (Mezgebe et al., 2023). The adaptation (5) stage, which comes to a close, concentrates on making long-term adjustments to strengthen the manufacturing system's resilience in comparison to its state before a disruption (Bianco et al., 2023).

The aggregate number and relative proportion of MFGRES stages mentioned in our sample are calculated. More than one is discussed in several publications, leading to 316 MFGRES stage references from 182 papers. Fig. 8 presents the complete outcomes. The majority of papers concentrate on the stages of readying and protection, which partially departs from earlier studies. Kusiak (2020) analyzes different MFGRES definitions; his findings indicate that most researchers do not include readying-related elements, with protection emerging as the most important phase. This result is confirmed by Arinez et al. (2020), who claim that MFGD protection is the main focus of AI-based MFGRM solutions. However, previous studies reveal that "few research addressed the potential for adaptation after getting disrupted" (Tūtlys & Spöttl, 2021). A long-term view is frequently overlooked. This situation might make it more difficult for businesses to gain a competitive edge, which usually happens in later MFGRES stages (Kusiak, 2020). In this regard, it's critical to keep in mind that a company's performance in later stages is influenced by its MFGRES in the pre-and early stages of disruption (Tūtlys & Spöttl, 2021).

Overall, the attention paid to the readying stage by MV-based Q4.0 MFGRES solutions is unexpected. Due to proactive manufacturing risk management's reputation as "rather ambiguous yet time and cost-intensive" (Oduoza, 2020), earlier research has different priorities. But according to our sample, this belief might shift with MV-based Q4.0. The novel methods allow for a "specific look-ahead" by creating "an interconnected and immersive virtual infrastructure" (Yao et al., 2022), allowing for more focused proactive approaches. In conjunction with utilizing the affordability of metaverse enabler technologies (Dincelli & Yayla, 2022; D. Shin, 2022), businesses may increasingly take advantage of virtual opportunities and change the emphasis of their MFGRES strategies from reactive to proactive.

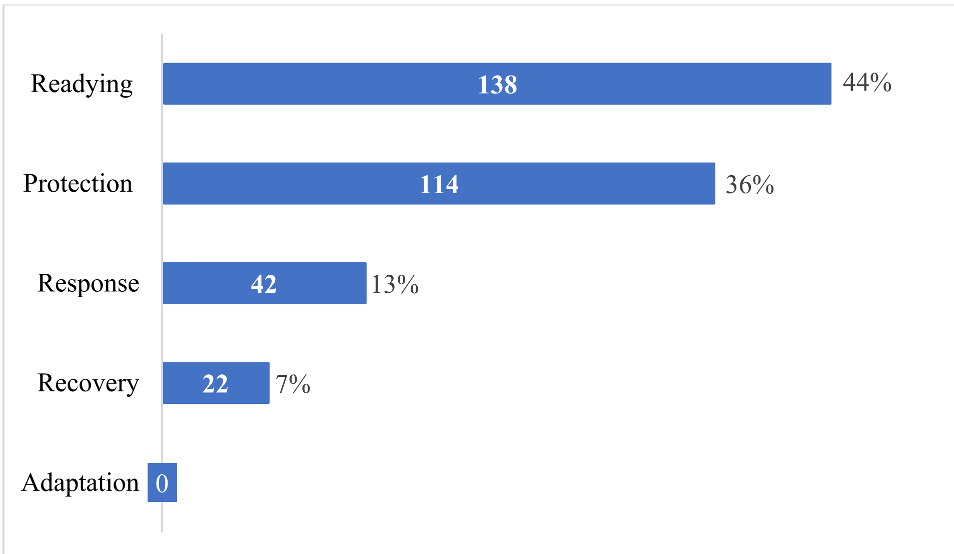

Fig. 8. Aggregate value and relative proportion of MFGRES stage references

2.5.5. Metaverse based Quality 4.0 manufacturing resilience framework

We examine our sample thoroughly in this section, integrating the knowledge from earlier sections and drawing relationships between MV-based Q4.0 enabler applications, MFGRES antecedents, and benefited MFGRES stages. Furthermore, we present our pyramidal MV-based Q4.0 MFGRES framework (Fig. 9), which illustrates the relationships and hierarchical structure that have been discussed by using MV-enabled Q4.0 applications as a key building block.

Transparency (s) is identified as the only MFGRES antecedent that all MV-based Q4.0 enabler applications promote. Overall, the metaverse applications will offer immutability, openness, reliability, and user control, resulting in a virtual environment that is more reliable and accountable (Lin et al., 2022; Queiroz et al., 2023). Regarding AI (s.E), deviations and defects from quality standards can be detected promptly. In a specific case of AI enhancing transparency, Sharma et al. (2022) use data mining techniques to extract insightful information, detect patterns, and identify anomalies, giving manufacturers a better understanding of their operations. The same holds true for processes that BC (s.A) has digitalized by enabling an atmosphere of trust where information and interactions can be proved and examined by manufacturers (Lin et al., 2022).

Using IoE applications (s.I) and CC (s.H) to submit the necessary data for AI and BC will increase transparency across every facet of the manufacturing process and provide an in-depth understanding of their operations (Banerjee, 2019; Borowski, 2021). By leveraging BDA (s.F) and statistical techniques, manufacturers can detect patterns and correlations that lead to quality issues (Papadopoulos et al., 2022). Since there is transparency in ensuring the preservation of high-quality products, manufacturers are able to take proactive steps to address quality problems. Technologies like VR (s.C) and MR (s.D) may replicate manufacturing processes and scenarios, enabling businesses to assess and improve operations (Steiner et al., 2023). In addition, manufacturers can evaluate the effects of process changes, test various scenarios, and pinpoint areas for improvement by developing virtual simulations (Yao et al., 2022). In this scenario, AR (s.B) can overlay safety guidelines and alerts onto actual environments, fostering openness in risk management and safety procedures (Zhu et al., 2019). Finally, DT (s.G) enhances overall operational efficiency by facilitating end-to-end visibility and optimization of manufacturing processes (Bordegoni & Ferrise, 2023). In general, we discover references asserting that the first four MFGRES stages can be enhanced through metaverse-enhanced transparency.

With the exception of DT, we conclude that all MV-based Q4.0 enabler applications might increase flexibility (t). Agile factory layout planning is made possible by VR (t. C) and MR (t. D). Manufacturers can quickly modify their factory setups to meet changing manufacturing requirements and adaptability in their manufacturing operations by visualizing and simulating various layout options (Berg & Vance, 2017; Dincelli & Yayla, 2022). In this setting, AR (t.B) makes use of VR and MR to deliver virtual environments for design and prototyping, simulation capabilities, tools for remote teamwork, on-demand information access, and training platforms (Wang & Dunston, 2006; Zigart & Schlund, 2020). By leveraging these technologies, manufacturers can improve processes, rapidly adapt to changing production demand, and make informed decisions, ultimately increasing manufacturing flexibility (Fast-Berglund et al., 2018; Gong et al., 2021). Using BC (t.A), manufacturers can increase their responsiveness, agility, and ability to change their production processes to meet changing market demands (Lin et al., 2022). BDA (t.F), AI (t.E), and IoE (t.I) together promote connectivity and integration across manufacturing operations (Lazaroiu et al., 2022; Özdemir & Hekim, 2018a). Data is gathered by IoE devices from a variety of sources and processed by BDA (Shilpa et al., 2019). This data is analyzed by AI algorithms to produce useful knowledge (Lazaroiu et al., 2022). By combining these technologies, a connected ecosystem is created that enables manufacturers to access and act on real-time information, facilitating swift decisions and flexible operations (Ma et al., 2022). Furthermore, CC (t.H) gives manufacturers access to real-time data and analytics devices (Bose et al., 2022). Manufacturers are able to gather and analyze data in real-time through the connection of IoT devices and sensors to the cloud, which enables them to make quick decisions, address problems as they arise, and optimize operations for greater flexibility (Darwish et al., 2019). Thus, one of the most important antecedents that supports the first four MFGRES stages is flexibility.

According to our sample, seven MV-based Q4.0 enabler technologies improve communication (u). The collaboration and information exchange between the various stakeholders involved in the manufacturing process is facilitated by CC (u.H) (Kochovski et al., 2020). By means of cloud-based collaboration tools, manufacturers can safely share documents, data, and insights with partners, suppliers, and customers (S. Shin et al., 2021). In BDA (u.F) and AI (u.E) applications, specific mechanisms enable communicating and condensing key findings on risks and manufacturing disruptions to all pertinent manufacturing stakeholders (Bag et al., 2023; Özdemir & Hekim, 2018b). In such a scenario, BC (u.A) can be crucial in sharing and collaboratively processing information (Lin et al., 2022). Overall, adding specific data obtained from IoE (u.I) devices can enhance information sharing (Shilpa et al., 2019). Moreover, AR (u. B) and MR (u. D) present a new communication option by immersively visualizing and sharing information, enabling remote collaboration and assistance, facilitating training and skill development, promoting design and prototyping processes, and enhancing inspection processes and quality assurance (Fast-Berglund et al., 2018; Gong et al., 2021). We find evidence that Q4.0-MV enabled communication has a beneficial effect on readying, protection, and response for the affected MFGRES stages.

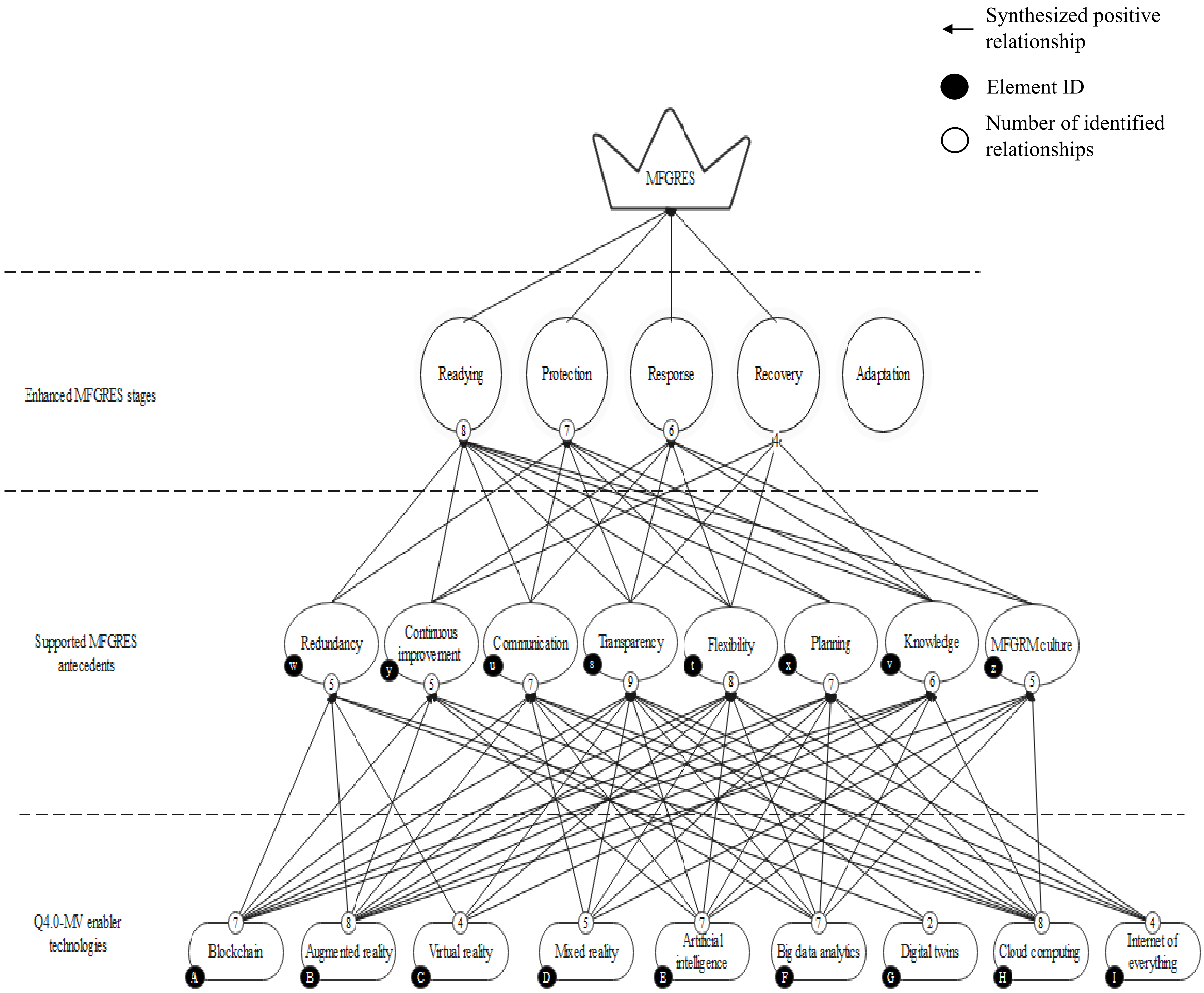

Fig. 9. Q4.0-MV MFGRES framework

Planning (x) processes can be enhanced by seven MV-based Q4.0 enabler technologies. Huge amounts of data from different sources can be gathered, processed, and analyzed using BDA (x.F) and AI (x.E) (Bag et al., 2023; Özdemir & Hekim, 2018b). By utilizing the power of AI algorithms and advanced analytics, planners can gain important insights into historical patterns, consumer behavior, and changing market conditions (Lazaroiu et al., 2022; Sharma et al., 2022). With the aid of data-driven, sophisticated algorithms, planners can simulate different scenarios, evaluate their viability, and comprehend the potential risks and opportunities linked to each scenario (Acerbi et al., 2021; Arinez et al., 2020). This ability aids in proactive, flexible planning decisions, taking into account various contingencies, and enhancing plans for better results (Chen et al., 2022). Furthermore, IoE (x.I) and sensor networks offer real-time oversight and visibility into different aspects of the planning process (Shilpa et al., 2019). Key performance indicators, resource usage, and real-time alerts and notifications are all available to planners. With this real-time visibility, they can spot bottlenecks, highlight deviations from the goals they had set, and quickly adjust to ensure plan conformity and maximize resource allocation (Miraz et al., 2015; Pelton & Singh, 2019). Planning scenarios, simulations, and data can be visualized more intuitively and interactively using MR (x.D) and AR (x.B) (Fast-Berglund et al., 2018; Gong et al., 2021). Planners can also perform virtual tours, assess spatial layouts, and spot potential problems thanks to MR and AR technology; this makes planning more effective and efficient (Adams, 2022; Berg & Vance, 2017). CC (x.H) and BC (x.A) improve planning processes by offering real-time data access and interaction, transparency and trust, scalable storage, execution automation through smart contracts, and improved data security (Dey et al., 2022; Krishnaraj et al., 2022). By applying these technologies, planners can enhance collaboration, streamline planning processes, make data-driven decisions, and guarantee the accuracy and reliability of planning data and transactions (Grassi et al., 2020; Leo Kumar, 2019). Overall, planning that is supported by MV-based Q4.0 can make it easier to achieve MFGRES during the readying and protection phases.

Knowledge (v) can be empowered by six MV-based Q4.0. Workers may acquire knowledge and perform complex tasks in a virtual environment with the help of AR (v.B) and VR (v.C); these offer immersive and interactive experiences (Gong et al., 2021; Vasarainen et al., 2021). Workers can use AR to superimpose digital data onto actual objects, providing real-time instructions, guidance, and annotations (Zigart & Schlund, 2020). VR enables lifelike simulations and virtual tours that make it easier to review designs, improve processes, and spot mistakes (Berg & Vance, 2017). By providing workers with contextual knowledge, AR and VR increase efficiency, quality, and safety (Adams, 2022; Morimoto et al., 2022). AI (v.E) gives manufacturers the ability to use data and automation to gain insights, predict the future, and improve processes (Arinez et al., 2020). Furthermore, the machine learning algorithm introduced by Rai et al. (2021) can examine enormous amounts of manufacturing data to spot trends, anomalies, and optimization possibilities. In general, AI-powered systems can automate monotonous tasks like inventory management, maintenance planning, and quality control, freeing up human resources for tasks with greater value (Acerbi et al., 2021; Sharma et al., 2022). In such a scenario, BDA (v.F) enables manufacturers to derive insightful information from huge and varied datasets (El Jaouhari, Arif, et al., 2022; Majeed et al., 2021). By analyzing data from a variety of sources, including sensors, customer feedback, and production systems, manufacturers can spot trends, streamline processes, and reach data-driven decisions (Grassi et al., 2020; Kurfess et al., 2020). CC (v.H) gives manufacturers access to vital information and resources from any location, promoting agility, scalability, and efficient teamwork (Bose et al., 2022; P. Kumar & Kumar, 2019). BC (v.A) promotes collaboration and innovation among manufacturers by facilitating the efficient and secure sharing of intellectual property (Jaouhari et al., 2023; Lin et al., 2022). In our sample, we discover proof that the first four MFGRES stages are improved by MV-based Q4.0-enabled MFG knowledge.

Five MV-based Q4.0 enabler technologies support continuous improvement (y). Transparency and traceability are made easier by BC (y.A) throughout the manufacturing process (Li et al., 2020). Every stage of production can be tracked and recorded by manufacturers, ensuring the accuracy and integrity of data (Banerjee, 2019; Iranmanesh et al., 2023). By identifying inefficiencies, bottlenecks and quality problems, this transparency enables manufacturers to make targeted improvements (Parker & Bach, 2020). The effectiveness and efficiency of training and maintenance processes are improved by AR (y.B) (Zhu et al., 2019). By enabling quicker detection and resolution, AR-based maintenance and troubleshooting solutions minimize downtime (Zigart & Schlund, 2020). AR also encourages continuous improvement in operational efficiency, reliability, and effectiveness by providing workers with contextual information and guidance (Steiner et al., 2023). BDA (y.F) and AI (y.E) give manufacturers the ability to glean important insights from sizable and varied datasets (Özdemir & Hekim, 2018b). On the one hand, manufacturers can spot trends, patterns, and opportunities for improvement by studying quality metrics, production data, and customer feedback (Bag et al., 2023). On the other hand, BDA and AI offer insight into operational performance, pinpoint the source of problems, and promote data-driven decision-making for process improvements (Benzidia et al., 2021). This encourages manufacturers to track key performance indicators (KPIs) and put corrective measures in place for ongoing improvement (Kamarthi & Li, 2020; Rai et al., 2021). CC (y.H) also offers scalable computing and storage resources to manufacturers, facilitating effective data management and analysis (Kochovski et al., 2020). Simultaneously, cloud-based collaboration platforms encourage knowledge sharing and cross-functional cooperation, supporting initiatives for continuous improvement (Bose et al., 2022). Based on our sample, we discover evidence that MV-based Q4.0 enabled MFG continuous improvement is particularly well-suited for assisting MFGRES in the readying, response, and recovery stages.

Five MV-based Q4.0 enabler technologies aid businesses in enhancing their MFGRM cultures (z). Real-time visualization and contextual data are provided by MR (z.D) and AR (z.B), which enhance situational awareness and enable proactive risk management (Fast-Berglund et al., 2018; Gong et al., 2021). In order to identify potential risks and take the appropriate safety measures, workers can overlay digital information, warnings, and safety measures onto their physical environment (Birkel & Hartmann, 2020; Oduoza, 2020). AR can also simulate dangerous scenarios or offer virtual training to enhance safety awareness and response (Vasarainen et al., 2021). AI (z.E) analyzes massive amounts of data to find patterns and forecast potential risks, which has a significant impact on risk management (Lazaroiu et al., 2022). Besides, the machine learning algorithm presented by Rai et al. (2021) can examine historical data, sensor readings, and other pertinent data to find anomalies, forecast equipment failures, and pinpoint safety risks. In this context, based on AI-powered risk analysis, AR can offer real-time security tips, while BDA (z.F) can continuously track and assess safety-related data gathered by MR and AR devices (Gong et al., 2021; Morimoto et al., 2022). Finally, CC (z.H) makes it possible to store, process, and collaborate on risk-related information and makes it easier to integrate these technologies into risk management procedures (Kochovski et al., 2020; S. Shin et al., 2021). Based on our sample, we find proof that MV-based Q4.0-enabled MFGRM cultures are particularly well suited for supporting MFGRES in the readying and response stages.

Five MV-based Q4.0 enabler technologies improve MFG redundancy (w). Through ongoing data collection from physical assets, DT (w.G) can serve as backup systems (Tao et al., 2019). Manufacturers can switch to DT in the case of a failure or disruption to maintain continuous operations, examine the underlying cause of the problem, and simulate alternative outcomes for rapid recovery (Zhu et al., 2019). Furthermore, remote assistance in problem-solving and troubleshooting can be provided by AR (w.B) and VR (w.C) (Sadhu et al., 2023; Vasarainen et al., 2021). VR and AR can offer a virtual presence in the event of disruptions or restricted physical access, enabling top management to direct on-site staff and guarantee the continuation of operations and maintenance (Berg & Vance, 2017; Dincelli & Yayla, 2022). By distributing computing and data storage resources, CC (w.H) and BC (w.A) offer redundancy and resilience (Dey et al., 2022; Krishnaraj et al., 2022). On the one hand, manufacturers can store crucial information, programs, and procedures in the cloud, ensuring that redundancy controls are in place (J.-L. Liu et al., 2019). Cloud-based systems can guarantee continuous access to applications and data in the case of local system disruptions or failures (Grassi et al., 2020). On the other hand, BC makes sure that data is replicated across a number of network nodes by using a decentralized and distributed ledger (Li et al., 2020). These MV-based Q4.0-enabled technologies offer redundancy measures that increase the robustness and accuracy of manufacturing processes, thereby enhancing system resilience. In our sample, we discover proof that the first two MFGRES stages benefit from MV-based Q4.0 enabled MFG redundancy.

3. Discussion

This paper looks at the different MV-based Q4.0 enabled technologies used in MFGRES and how MV-based Q4.0 can be utilized to transform practices in this area. In the current scenario, manufacturing organizations must establish virtual manufacturing techniques and smart capability development in order to take advantage of the expected advantages of the metaverse journey. Since the MV-based Q4.0 concept enables improved comprehension and achievement of manufacturing flexibility, accuracy, and resilience (Lin et al., 2022; Queiroz et al., 2023), smart practices typically have a greater impact during times of crisis. When unexpected events like Covid-19 occur, virtual manufacturing promotes adaptable actions that enable performance stability in manufacturing processes (Berg & Vance, 2017; Krauß & Kärger, 2022). According to Cali et al. (2022), MV-based I4.0 can take advantage of the results of conventional operations and turn them into virtual operations. Greater reliability, accuracy, and responsiveness enable performance levels to be maintained even in times of crisis, preventing performance degradation (Steiner et al., 2023; Yao et al., 2022).

In line with the final step of our SLR approach, we discuss our MV-based Q4.0 MFGRES framework in the context of disruption to demonstrate its practical applicability. Given that COVID-19 is regarded by academics as causing one of the worst manufacturing disruptions ever (Belhadi et al., 2021, p. 19; J. Yang et al., 2022, p. 19), this event is a good reference point. This evaluation is made because a pandemic differs from other manufacturing disruptions in certain ways. Previous studies extensively discuss the various risk types identified during disruptions, including risks related to the availability of resources, operations, and customer demands (Bianco et al., 2023, p. 19; Njomane & Telukdarie, 2022, p. 19). However, the pandemic's dimensions and concurrent occurrence of the risks make this a special occurrence (Allam et al., 2022, p. 19; Kamarthi & Li, 2020, p. 19). In order to categorize a pandemic, Craighead et al. (2020) identified three traits: scope, spillover, and shifts. They claim that the COVID-19 pandemic has disrupted numerous industries (scope), various sectors and geographies over time (spillover), and has caused significant volume and variety fluctuation in demand and supply (shifts). Similar arguments are made by (Kamarthi & Li, 2020, p. 19), who emphasize the extreme and concurrent effects of the global pandemic on numerous manufacturing stakeholders and regions, as well as its unheard-of length of time. This lengthy period of disruption is referred to as a "crisis-as-a-process" by (Mezgebe et al., 2023, p. 19) as opposed to a "crisis-as-an-event."

According to existing literature, organizations seeking to increase their performance must constantly evaluate their manufacturing designs and take both proactive and reactive measures (re-configuration) to address manufacturing vulnerabilities (Hashemi-Petroodi et al., 2021; Wan et al., 2018). Resilience refers to a company's capacity to maintain planned operations and ensure global performance stability in the wake of a disruption (or a series of disruptions) (S. Kumar & Anbanandam, 2020). According to Hosseini et al. (2016), resilience traits have a positive impact on performance. Thus, it is assumed in this study that operational performance (e.g., quality, wastage, productivity), supply chain performance (e.g., shortage of raw materials, lead time,), and financial performance are related to the ability of manufacturing companies to withstand disruptive events. In light of this, the study makes the assumption that resilience reduces the impact of disruption's negative effects on manufacturing operations and efficiency.

Of note, academics concur that long-standing MFGRES antecedents benefit businesses in overcoming disruptions. For example, according to some research (Bianco et al., 2023; Longo et al., 2022), transparency and communication have been essential antecedents for supporting MFGRES throughout this crisis. Accordingly, by utilizing cutting-edge virtual technologies and digital transformation, manufacturers could maintain operational effectiveness, adjust to disruptions, and guarantee product quality and customer loyalty in a rapidly changing environment (Fast-Berglund et al., 2018; Yao et al., 2022).

We use our MV-based Q4.0 MFGRES framework on a use case in the automotive industry, in particular Contract Manufacturing (CM), in order to better understand the role that MV-based Q4.0 and MFGRES antecedents play during disruptions. We choose this industry because manufacturing in the automotive sector has historically been susceptible to supply chain disruptions. According to recent studies (Abdel-Basset & Imran, 2020; Ashjaei et al., 2021), just-in-sequence and just-in-time production, as well as mass customization and high levels of outsourcing, are all prevalent in automotive supply networks, making them extremely globalized and complex.

During the COVID-19 pandemic, CMs have encountered a number of difficulties. Due to factory closures, transportation boundaries, and shipment delays brought on by the pandemic, manufacturing was disrupted (Frieske & Stieler, 2022). This had an effect on production schedules and delivery commitments by increasing lead times and causing shortages of essential components (J. Yang et al., 2022, p. 19). While other CMs saw a sharp decline in orders, some saw a surge in demand for necessities (Belhadi et al., 2021). It became difficult to control the fluctuation and volatility of demand, necessitating quick changes in production capacity, inventory levels, and workforce (A. Kumar et al., 2020). Following the lockdown, the automotive sector was seen as a driver of economic growth due to rising demand (Frieske & Stieler, 2022; Hoeft, 2021). These unanticipated shifts in demand encouraged a bullwhip impact on the automotive sector. In general, the automotive sector serves as a prime example of how a pandemic can simultaneously affect supply and demand (Belhadi et al., 2021).

During a virus outbreak, transparency is essential (A. Kumar et al., 2020, p. 19). The use of AI (s.E) and BDA (s.F) based early warning systems that assess the situation at the infection source and determine preventative measures can be beneficial, particularly for geographically remote facilities. Transparency is also a key antecedent for making the right decisions in response to supply shortages. The full potential of the BC (s.A), AR (s.B), and CC (s.H) can be used by CMs to track the entire process of goods, assemblies, and components in the manufacturing facility. Better decision-making and preventative measures may be made possible by increased transparency regarding safety stocks, manufacturing capabilities, or quality control and security. Also, BC (v.A) and CC (v.H) can be used to strengthen the understanding of a CM's end-to-end manufacturing system and enhance supply conditions. Most CMs lack a thorough map of their entire supply chain, making it difficult to identify potential low-tier suppliers who may be impacted. Communication delays occur because the first-tier supplier frequently alerts the CM to disruptions. In these circumstances, information sharing and collaboration are supported by AR (y.B) and BDA (v.F). These MV-based Q4.0 applications are also designed to function primarily on their own; this is a clear benefit during a pandemic when the capacity of human employees may be limited. Other manufacturing bottlenecks can also be quickly identified using DT (w.G) and AR (w.B). For instance, border closures, a frequent response to pandemics (Ahmed et al., 2023, p. 19), can be quickly identified and prepared actions taken (e.g., VR can assist in visualizing and analyzing the manufacturing network in a virtual environment). Manufacturers can find alternative routes, improve inventory management, and make contingency plans by mapping out the various logistics and production stages. The combination of all these attributes and data can be used to build a digital manufacturing twin (Gohari et al., 2019), which would enable thorough and real-time transparency and an in-depth understanding of a CM during a virus outbreak. In addition to enabling virtual representations, MR (x.D) solutions also enable using the digital manufacturing twin to evaluate various use cases. This is a crucial aspect because infection occurrences during a pandemic can be extremely dynamic, necessitating routine reevaluations of manufacturing metrics.

Geographic diversification has also been shown to be crucial during pandemics. AI (x.E) based tools can determine the best supplier locations based on distinct country risk scores so that this factor can be taken into account when choosing suppliers (Lazaroiu et al., 2022). By proactively implementing AR (x.B) solutions at the CM's production site, it is also possible to lessen the likelihood of supply shortages for specific parts (Angelopoulos & Mourtzis, 2022). Once more, the COVID-19 pandemic has highlighted difficulties for demand forecasting, manufacturing continuity, and supply reliability. Increased use of virtual factories in manufacturing facilities and distribution centers may speed up the implementation of infection control procedures and possibly avert site closures (Morshedzadeh et al., 2022). Finally, by using BDA (s.F) to analyze internal and external data, demand fluctuations can be detected earlier, helping to improve forecast accuracy, fostering trust among manufacturing partners and minimizing the bullwhip effect (El Jaouhari, Alhilali, et al., 2022).

Recent studies have begun to empirically demonstrate the effectiveness of MV-based Q4.0 technologies for boosting MFGRES during disruptions. According to Belhadi et al. (2021), the automotive industry views BDA, BC, and the IoE as crucial catalysts to meet the manufacturing challenges brought on by COVID-19. Industry experts believe utilizing these metaverse technologies is even more crucial than implementing traditional MFGRES measures like continuity plans or safety stocks. For instance, Lohmer & Lasch (2020) describe how a CM collaborates with a service provider to set up BC (s.A) material tracking in its complex SC. The company increased transparency of its MFG with this initiative. During the crisis, automotive companies used AI (s.E) to accurately predict the necessary levels of safety stock and production capacity (Belhadi et al., 2021). Lahnaoui et al. (2021) present a predictive analytics tool (s.E) to forecast car demand based on actual infection numbers in order to overcome market uncertainty. Experts predict that the automotive industry will swiftly adopt MV-based Q4.0 enabler technology for improved MFGRES in light of these positive outcomes from the COVID-19 pandemic (Belhadi et al., 2021). This is because upstream suppliers, in particular, continue to experience significant delays when implementing virtual technology to increase MFGRES (Fast-Berglund et al., 2018).

The CM use case emphasizes the extraordinarily important role played by MV-based Q4.0 in the context of MFGRES as well as the potential of enabler technologies to lessen the adverse effects of a disruptive event. We assert that MV-based Q4.0 technologies ought to be able to help MFGRES in those situations because the risks seen during the COVID-19 pandemic can also materialize during other manufacturing disruptions.

4. **Implications of the study**

Fig. 10 is an illustration of crucial implications in the triple helix actors (academia, industry, and governments) resulting from our MV-based Q4.0 MFGRES framework.

4.1. Theoretical implications

We present the following major areas as requiring further research considering our findings and discussions. We draw the conclusion that AI is the most advanced and cutting-edge MV-based Q4.0 technology in MFGRES after carefully reading the papers reviewed in this study. Researchers should think about using the data produced by the various manufacturing structures as the foundation for future studies. Scholars could suggest, based on actual manufacturing data, which MV-based Q4.0-enabled technologies are best suited to achieve MFGRES. Currently, many researchers (Almada-Lobo, 2015; Bauer et al., 2021; Marinagi et al., 2023), examine various MV-based Q4.0 enabled technologies for MFGRES before comparing the results to determine which technology performs more effectively for the bottleneck and issue under consideration. The results of this study also shed light on a wider range of less common MV-based Q4.0 enabled technologies that might become more significant in subsequent research.

4.2. Practical implications

Future studies should look at virtualized production environments in relation to the use of MV-based Q4.0 for improved operations management across various industries and sectors. MV-based Q4.0 is frequently used to address on-demand manufacturing and customization; this is primarily due to the possibility of mistakes in decisions made manually. Every manufacturing task involves decision-making, so it shouldn't be limited to production planners. As a result, other manufacturing fields should be investigated, and decision support tools should be improved. Future research should assess how the adoption of MV-based Q4.0 has affected the labor force. Understanding how MV-based Q4.0 integration might affect the workforce is essential for preserving the proper balance between all the parts of a manufacturing process.

More frequently, executives in MFG and related industries deal with MFGDs, and are looking for new solutions that reduce their effects. When these practitioners identify weaknesses in particular MFGRES antecedents, they can use our framework to determine the best MV-based Q4.0 enabler technologies. Moreover, MFG partners can use this framework as a point of departure for cooperation and negotiations. The study's findings can also assist managers in anticipating and addressing manufacturing challenges by implementing techniques that build distinctive capabilities when crisis situations demand quick adjustments. We also identify technological synergies that can assist managers in creating systems supporting multiple technologies in MFGRES. Further, we highlight the crucial role that employees' digital skills, problem-solving abilities, and creative thinking play in achieving the full potential of MV-based Q4.0. This evidence gives forward-thinking managers a strong case for investing in metaverse education programs. Finally, future research may compare the effectiveness of various MV-based Q4.0-enabled technologies and techniques in order to help practitioners choose the best MV-based Q4.0-enabled technologies for their manufacturing process.

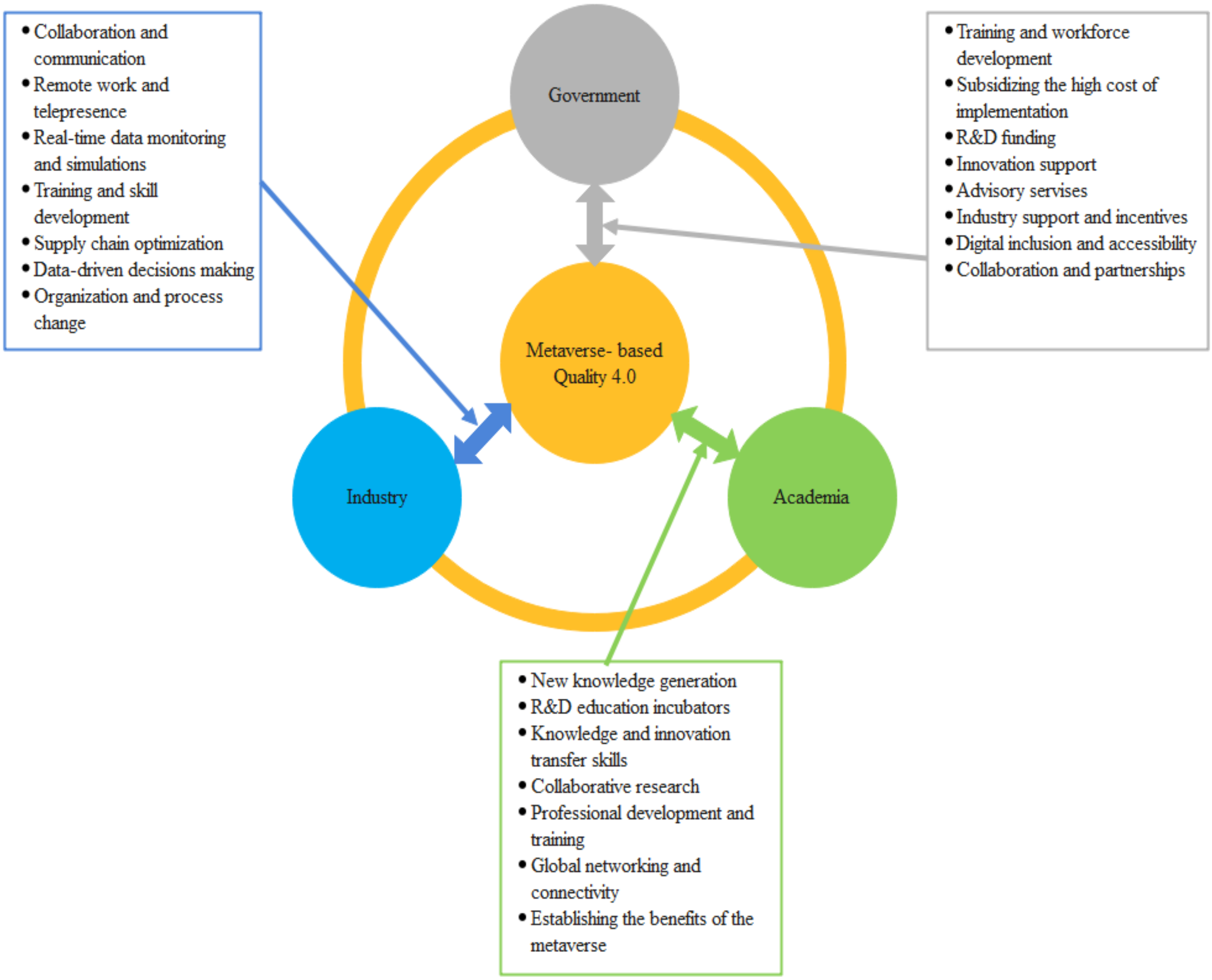

Fig. 10. Triple helix framework for MV-based Q4.0 implications

5. Conclusion

We present a thorough and mutually exclusive classification of MV-based Q4.0 enabler technologies supporting MFGRES using an SLR method. Thus, we can respond to SRQ1 by saying that while all of the technologies mentioned have the potential to support MFGRES, AI is the most developed and up-to-date one. In addition, by analyzing the relationship between MFGRES antecedents and MV-based Q4.0 enabler technologies, we fill a significant research gap. We find strong evidence that MV-based Q4.0 will strengthen MFGRES antecedents, and we provide a sophisticated MV-based Q4.0 MFGRES framework. Using our framework, we can also address SRQ2. A variety of MV-based Q4.0 enabler technologies have the capability to improve, in particular, transparency and flexibility, on a large scale. Although the range of appropriate enabler technologies is more constrained, redundancy, planning, continuous improvement, and an MFGRM culture can all be supported. We discover that in relation to SRQ3, current research at the MV-based Q4.0 and MFGRES intersections emphasizes solutions that support the first three MFGRES stages. In contrast, recovery and adaptation remedies still need to be completed. We address SRQ4 by outlining a use case for an automotive CM, demonstrating the high potential of MV-based Q4.0 enabler technologies to reduce pandemic risk.

In our study, we try to cover all the MFGRES stages and antecedents and the effect of MV-based Q4.0-enabled technologies on MFGRES practices. These MFGRES stages and antecedents are classified, and the corresponding relationship of MV-based Q4.0-enabled technologies in these MFGRES stages and antecedents is identified. The quantitative data reveals that the MFGRES stages and MFGRES antecedents considerably adopt the MV-based Q4.0-enabled technologies in various significant capacities to improve their MFGRES practices. However, the proposed framework remains in the development stage because MFGRES practices require time; integrating these practices via MV-based Q4.0 requires high computational performance. We provide all the technologies that have been utilized so far for MFGRES practices.

The framework created in this study will be helpful for researchers and practitioners who want to conduct more in-depth studies in this field. Researchers can identify gaps in recent papers on the application of MV-based Q4.0 in MFGRES using the information presented above and conduct additional can-do studies.

5.1 Limitations and suggestions for future research

The limitations of the study and future research directions are discussed in this last section.

Firstly, the inclusion criteria used and the database used have an impact on SLR results. Even though we think we have unearthed all pertinent contributions, it's still possible that we have missed certain research studies. However, we are confident that more research papers would not undercut the study's conclusive findings.

Secondly, we develop a framework using relationships found in earlier research between MV-based Q4.0 applications, MFGRES antecedents, and MFGRES stages. Due to the nature of SLRs, we do not assess the effectiveness of the relationships in this study. However, a performance quantification may be included under the current framework. A disruptive event, in our opinion, serves as an appropriate framework for the various assessments, and we, therefore, call for empirical confirmation. The advancement of research will assist academics and managers in setting priorities and safely selecting particular cutting-edge technologies to meet specific MFGRES targets with limited resources.

Thirdly, the current results support the fact that the majority of MV-based Q4.0 enabler technologies are still under-represented in MFGRES research. To fully realize the potential of the metaverse, we propose additional theoretical and real-world application examples for VR, MR, AR, CC, BC, and DTs. We especially encourage contributions that combine a number of cutting-edge technologies in order to maximize the benefits of each technology and create synergies. Our framework, which is far from complete, can be developed further with research in this direction.

Fourthly, when examining the intersections of MV-based Q4.0 and MFGRES, we find an obvious lack of long-term orientation. This might make it more difficult to gain a competitive edge following an MFGD (Yao et al., 2022). Therefore, we support metaverse research that focuses on helping MFGRES during its adaptation and recovery stages.

Finally, we recommend an in-depth examination of MFGDs effects and the challenges that businesses will experience from this. This research also encourages studies that include front-line managers in assessing the effects MFGDs and the implementation of virtual manufacturing procedures in order to discover new effects of MFGDs for companies. Such investigations could make use of different stages of analysis or brand-new constructs/variables to monitor the effect of MFGDs over time. Furthermore, comprehensive case studies investigating the measures taken by businesses during MFGDs may aid in our understanding of how businesses should act, react and most importantly, prevent upcoming MFGDs.

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Appendix A. The abbreviations used throughout the paper.

Abbreviation	**Meaning**
AI	Artificial Intelligence

AR	Augmented Reality
BC	Blockchain
BDA	Big Data Analytics
CC	Cloud Computing
CPSs	Cyber-Physical Systems
DLT	Distributed Ledger Technology
DT	Digital Twins
I4.0	Industry 4.0
ICS	Industrial Control Systems
ICT	Information and Communication Technologies
IIoT	Industrial Internet of Things
IoE	Internet of Everything
IoT	Internet of Things
MFG	Manufacturing
MFGDs	Manufacturing Disruptions
MFGRES	Manufacturing Resilience
MFGRM	Manufacturing Risk Management
MR	Mixed Reality
MV	Metaverse
Q4.0	Quality 4.0
RQs	Research Questions
SC	Supply Chain
SLR	Systematic Literature Review
SRQs	Sub-Research Questions
VR	Virtual Reality