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Production & Manufacturing Research
An Open Access Journal

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tpmr20

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To cite this article: Gábor Nick, Klaudia Zeleny, Tibor Kovács, Tamás Járvás, Károly Pocsarovszky & Andrea Kő (2024) Artificial intelligence enriched industry 4.0 readiness in manufacturing: the extended CCMS2.0e maturity model, Production & Manufacturing Research, 12:1, 2357683, DOI: 10.1080/21693277.2024.2357683

To link to this article: https://doi.org/10.1080/21693277.2024.2357683

Published online: 20 Jun 2024.

PRODUCTION & MANUFACTURING RESEARCH
2024, VOL. 12, NO. 1, 2357683
https://doi.org/10.1080/21693277.2024.2357683

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Artificial intelligence enriched industry 4.0 readiness in manufacturing: the extended CCMS2.0e maturity model

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ABSTRACT

The manufacturing industry faces solid global competition, uncertainties, rapid technological advances, and disruptive events, forcing it to rethink production operations and improve its digitisation efforts. Several Industry 4.0 (4IR) readiness and maturity models are known, but the increasing opportunities offered by AI are not, or only partially, included in these models. This research uses a literature review and expert interviews to explore the role of AI methods and applications in relation to digital twins in production, manufacturing, and logistics. Based on this study and in line with the development phases of the Connected Factories project, the Company CoMpaSs 2.0e (CCMS2.0e) 4IR maturity assessment model was developed, including an AI dimension. The model was tested with four real production cases. The main contribution is that companies can use the proposed model to assess their 4IR readiness in artificial intelligence and identify related intervention points for improvement.

ARTICLE HISTORY
Received 12 August 2023
Accepted 13 May 2024

KEYWORDS
Maturity model; industry 4.0 readiness; artificial intelligence; digitization; digital twin

1. Introduction

1.1. Context

Artificial intelligence (AI) and machine learning have provided new opportunities for manufacturing operations to optimise productivity by gaining insights into industrial data (Rai et al., 2021). They support production pattern identification in the smart manufacturing paradigm and enrich decision support in several manufacturing and production applications. AI can also help increase companies' efficiency by using robots in manufacturing, optimising logistics systems, or improving maintenance by forecasting potential problems (Rathore et al., 2021). Connecting the real and virtual worlds is crucial in production, manufacturing, and logistics. Digital twins play a key role in this aspect; they visually represent a company's physical assets, facilitating improved decision-

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making, optimisation, prediction, and monitoring (Dolgui & Ivanov, 2023; Rasheed et al., 2020).

Industry 4.0 (4IR) represents the information-intensive transformation of manufacturing in a connected environment of humans, data, processes, services, systems and IoT-enabled industrial assets with the generation and utilization of usable data and information to create a smart industry of cyber-physical systems and the ecosystems of industrial innovation and collaboration (Nick et al., 2021). Industry 5.0 is the next phase in the evolution of industrial systems; it supports an industry beyond efficiency and productivity as the predominant goal and contributes to the „symbiosis" of industry and society (Xu et al., 2021). It complements the existing 'Industry 4.0' approach by specifically putting research and innovation at the service of the transition to a sustainable, human-centric and resilient industry. The concept of Industry 4.0 attributed significant importance to humans, who make decisions and direct operations as a central entity organizing production (Chander et al., 2022; Sidorenko et al., 2023). This role transforms Industry 5.0, as an increasing number of decisions are carried out by artificial intelligence.

1.2. Motivation

In the era of 4IR, pressured by crises such as the COVID-19 pandemic, organisations must develop their digitisation to remain competitive and resilient. This may mean different things to them, depending on their current situation and the goals they aim to achieve. Digitisation is a complex field where companies could benefit from some guidance, which is the exact role of 4IR maturity assessment models. Readiness and maturity models can support companies in various ways; they provide the starting point for business improvement (Akdil et al., 2018; Bertolini et al., 2019; Geissbauer et al., 2016; Gökalp et al., 2017; Nick et al., 2020; Rafael et al., 2020; Santos & Luís Martinho, 2019), but the AI dimensions are still not embedded in them. As artificial intelligence plays a crucial role in the future of 4IR and in building and improving the resilience of production, mitigating the effects of disruption should be included in maturity models (Dohale et al., 2022).

1.3. Problem statement and research objectives

Based on the analysis of Hajoary (2020). Santos and Luís Martinho (2019) and Angreani et al. (2020), neither the 4IR models' dimensions nor the most influencing maturity indicators include AI. Our research aims to fill this gap by extending the Company CoMpaSs 4IR maturity assessment model and tool (CCMS) (Nick et al., 2020) with AI dimensions. CCMS maturity model's most important output is a list of intervention points: recommended areas to work on to improve the company's digitisation. As technologies evolve, the tools that measure maturity must be updated, too, resulting in the fine-tuned CCMS2.0 (Nick et al., 2021). The role of AI was investigated for methods and applications concerning digital twins in production, manufacturing and logistics through a literature review and expert interviews. Based on the results of our literature review and experts' interviews, there is an evolving need to assess the application of AI in the company. According to this exploration and the development stages of the Connected Factories (CF) project (European Factories of the Future Research

Association [EFFRA], 2020) project, the CCMS2.0 maturity model is extended with an additional dimension related to AI.

CCMS2.0e is both a descriptive and prescriptive maturity model (Röglinger et al., 2012) that not only helps assess the 4IR status of the company but also provides improvement measures via the intervention points. For the maturity levels assigned to the dimensions, the authors are considering the levels determined by the Connected Factories (CF) project (EFFRA, 2020), which aimed to help companies navigate their digital transformation with elaborating pathways and cross-cutting factors between them. The extended CCMS2.0e model was tested in four real-world manufacturing cases. The main contribution is the CCMS2.0e model, which supports companies to evaluate AI-enriched 4IR readiness in manufacturing and identify the intervention points to progress.

This paper is structured as follows. Section 2 provides an overview of the research method. Section 3 presents the CCMS2.0e model. Section 4 is the discussion; it details the CCMS2.0e validation through cases. Conclusions are summarized in Section 5.

2. Methodology

Our research method consists of five steps (Figure 1). First, based on the literature review (step 1), experts' interviews (step 2), and lessons learned in the Connected Factories project (step 3), the research gaps are identified as input to update CCMS extension towards AI. Next, the new AI dimension is developed in the CCMS model (step 4), and finally, the new CCMS model is tested at four companies (step 5).

2.1. Selecting and analyzing the literature

The digital twin is becoming crucial for AI in intelligent manufacturing, improving efficiency and enabling new opportunities (Lv & Xie, 2022). Digital twins have a key role in the operation of cyber-physical intelligent systems; the recent hype of AI solutions in the industry bolsters their importance. However, the literature on AI in

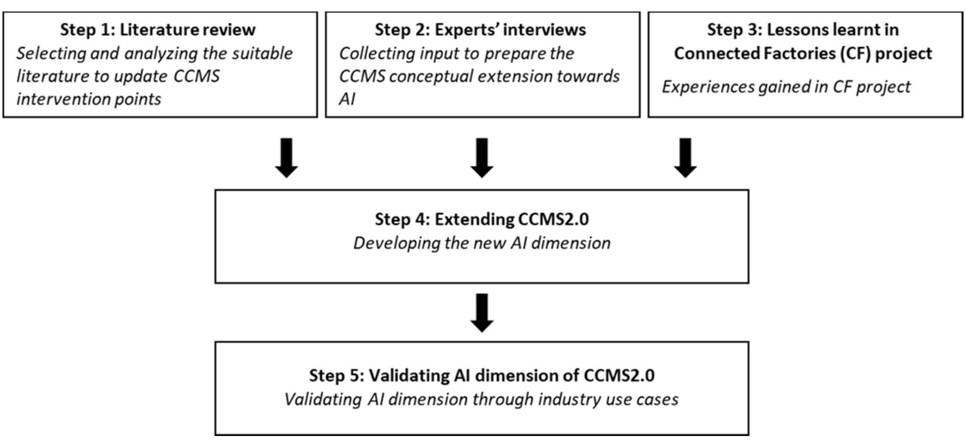

Figure 1. Research method.

digital twin production, manufacturing, and logistics is still preliminary and has only started growing recently. According to the Scopus database, most of the related scientific publications are between 2020 and 2023; their number started to grow in 2018. Surveys of this field are rare; we found a few related articles in Scopus (Bosch-Sijtsema et al., 2021; Minerva et al., 2020; Rasheed et al., 2020; Yitmen et al., 2021). The first step of our research process was performing a literature review to understand the role of AI methods and applications concerning digital twins, production, manufacturing and logistics, the relevant application fields that can be included in the maturity model's intervention points and the application levels of AI methods both in research and in industry. AI offers great potential for advances in many areas, but serious doubts exist about responsible and ethical decision-making as an awareness aspect of a company. Many ethical regulations, principles, and guidelines for responsible AI have been issued recently, but most of these are high-level and difficult to relate to practice. Responsible AI (RAI) and ethical aspects are important dimensions of the use of AI in companies. The list of literature was obtained from the largest abstract and citation database of peer-reviewed literature, Scopus; the search presented here was carried out in March 2023. Because digital twin is a core technology in Industry 4.0, the following query string is used: TITLE-ABS-KEY ('digital twin' AND ('artificial intelligence' OR 'machine learning' OR 'deep learning') OR ('supervised learning' OR 'unsupervised learning' OR 'reinforcement learning') OR ('regression' OR 'classification') OR ('IoT' OR 'sensor data' OR 'big data') AND ('manufacturing' OR 'logistics' OR 'production')) AND (LIMIT-TO (SRCTYPE, 'j')) AND (LIMIT-TO (DOCTYPE, 'ar')) AND (LIMIT-TO (LANGUAGE, 'English')). The search results were limited to journal articles whose language was English and that have been published since 2017; in total, 466 articles met these criteria. The following main research questions were defined in connection with a reviewed paper that was investigated in the literature review:

- Which topics is the article related to product design/development, optimisation, logistics, production network, or other?
- What method has been applied or proposed: deep learning, reinforcement learning, regression, classification, clustering, digital twin, simulation or some other? This section also examined whether no specific method is proposed or applied, but only a theoretical approach is presented.
- What are the trends in the number of papers presented in the above areas?

Several keywords were defined for each topic to answer the literature review-related research questions, and then the articles in which they appeared were counted using a Python script. To decide whether a keyword appears in an article, the author keywords, the index keywords, and the abstract fields were checked.

Selected articles were analysed using the text analytics method of VOSviewer. Text analytics is a common method for processing large text content (Demeter et al., 2019; Manikas et al., 2019) and scientific publications (corpus) to identify main trends and key research issues. It is widely used for information extraction, topic tracking, summarization, categorization, clustering, concept linkage, information visualization and question answering (Gupta & Lehal, 2009). VOSviewer is suitable for document clustering, visualising the content by creating bibliometric maps and displaying large text-based maps in an easy-to-interpret manner (van Eck & Waltman, 2011). The previous step of the literature review was extended with the text analytics method to determine clusters from the corpus and describe these clusters using bibliometric maps.

2.2. Literature review result

There has been a steady increase in academic research in AI applications in digital twin modelling since 2017 based on the 466 articles our literature search resulted (see Figure 2). It is in line with the results of (Rathore et al., 2021). The field of logistics is under-researched, while manufacturing and production appear more frequently. Most publications focus on production processes, product development and design.

The leading field of AI methods is deep learning (DL), as shown in Figure 3, DL is gaining popularity due to its supremacy in terms of accuracy when a large amount of data is used in the training phase (Lee et al., 2020).

In most articles, the leading concept proposes a theoretical approach, i.e. applying an artificial intelligence framework or architecture. However, the number of applications in

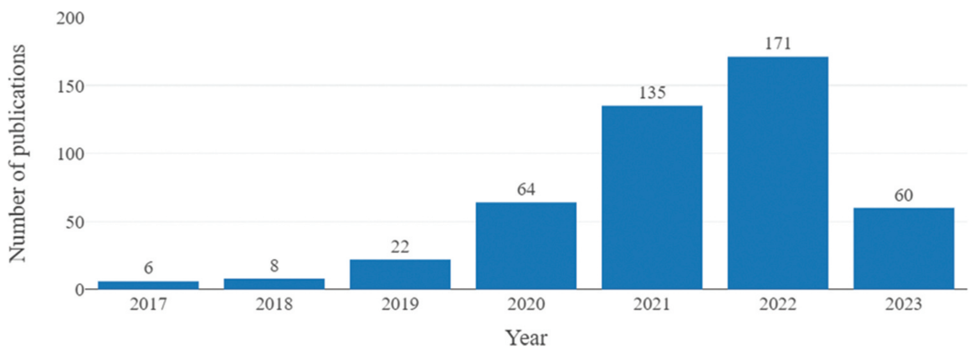

Figure 2. Number of publications in the field of AI applications and digital twins.

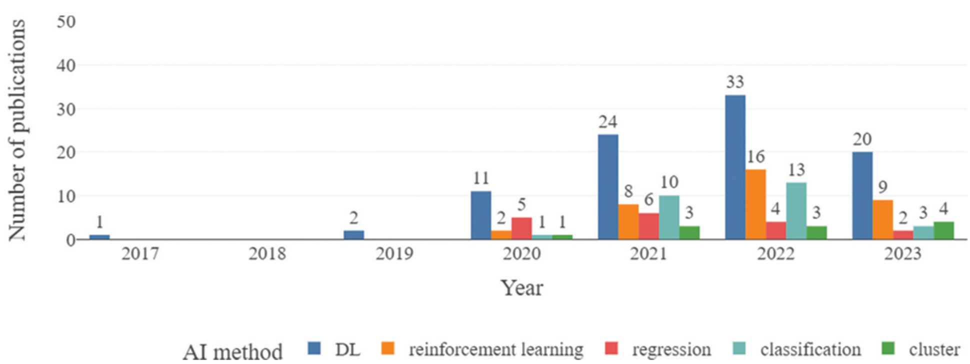

Figure 3. Number of publications by type of AI method.

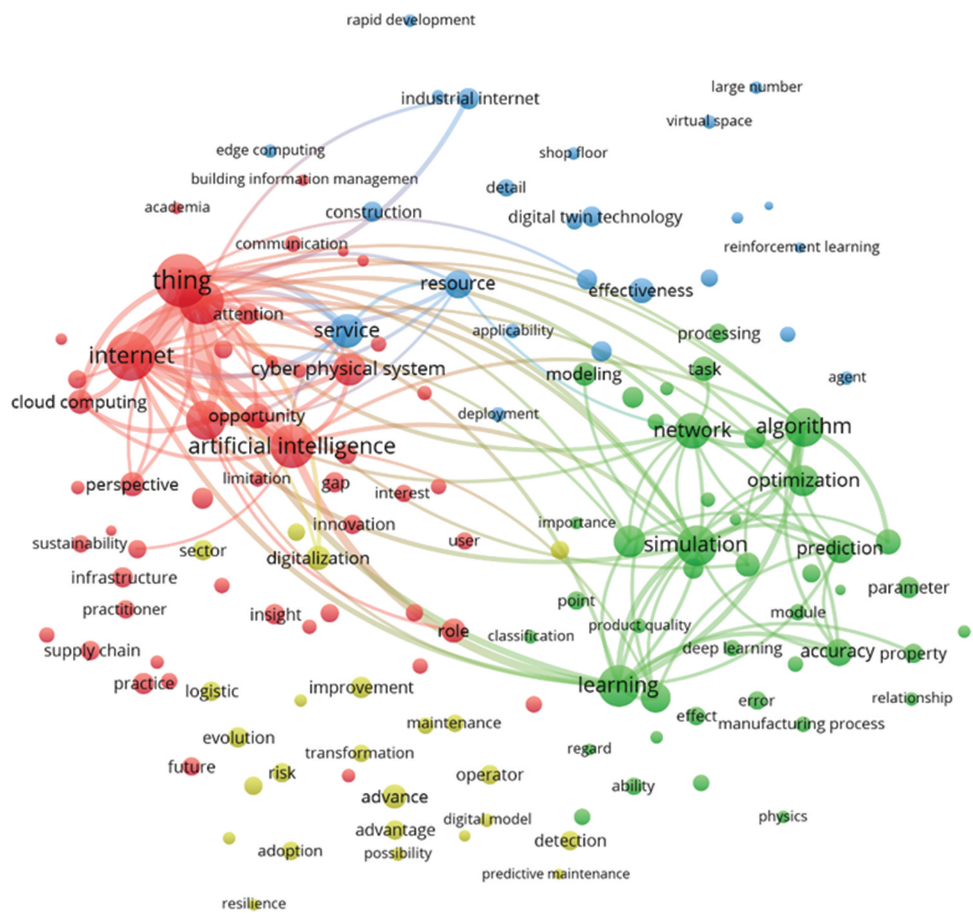

Figure 4. Clusters of concepts.

a real industrial environment is still lower than the number of theories. The examined publications rarely discuss data security and safety issues (approximately 12%).

The text analytics of the abstracts, keywords, and titles of the 466 articles related to digital twins and artificial intelligence in manufacturing and logistics revealed the clusters of concepts and how they are connected (Figure 4). Four clusters were identified; the first (red) could be described as the 'cyber-physical system'.

An important part of this cluster is the 'Internet of things' (in the Figure 4 highlighted as 'thing' and 'internet' where next to it the label for the term 'IoT' is not visible"), the network of physical objects, that is a crucial part of the equipment from AI point of view. The second cluster (green) is related to the 'learning' and the 'algorithms', virtual processes of simulation, optimisation and prediction. The third (blue) and the fourth (yellow) clusters are weakly connected to the first two. The third cluster is about the digital twin, while the fourth is about the potential benefits, predictive maintenance being an important part. The term 'artificial intelligence' is strongly connected to the terms 'learning', 'algorithm', and 'simulation', highlighting that learning through simulation could be the dominant application of artificial intelligence currently. Surprisingly, based on the text analytics 'digital twin' is weakly connected to the other concepts, meaning that it is not as embedded in the application of artificial intelligence as expected.

2.3. Experts' interviews

Second, experts were interviewed to prepare the CCMS2.0 conceptual extension towards AI. In total, 36 interviews were conducted with experts working or doing research in manufacturing, production, and supply chains. Twenty-four of them (66%) had a degree in engineering, twelve of them (33%) in economics and six of them (17%) in both. Ten interview participants (28%) had an MSc degree, and twenty-six (72%) had a PhD. These experts also considered practical recommendations and suggestions when formulating the new dimension in the CCMS model.

2.4. Experiences gained in the connected factories project

Connected Factories (European Factories of the Future Research Association, 2020) project aims to help factories transform into smart and connected ones. Pathways are developed with European experts and stakeholders to help factories navigate digital opportunities and challenges. Figure 5 shows the maturity levels and development pathways for a factory's generic digital transformation process.

Specific pathways show important milestones to realise a hyperconnected or collaborative product-service factory. Many factors or enablers, such as skills and business models, are pivotal for long-term transformation success. These cross-cutting factors are relevant for many milestones within the pathways. Despite the individual pathways of each factory, they play an important role along with many specific use cases. More pathways are being developed in the project's next step, covering circular economy, AI

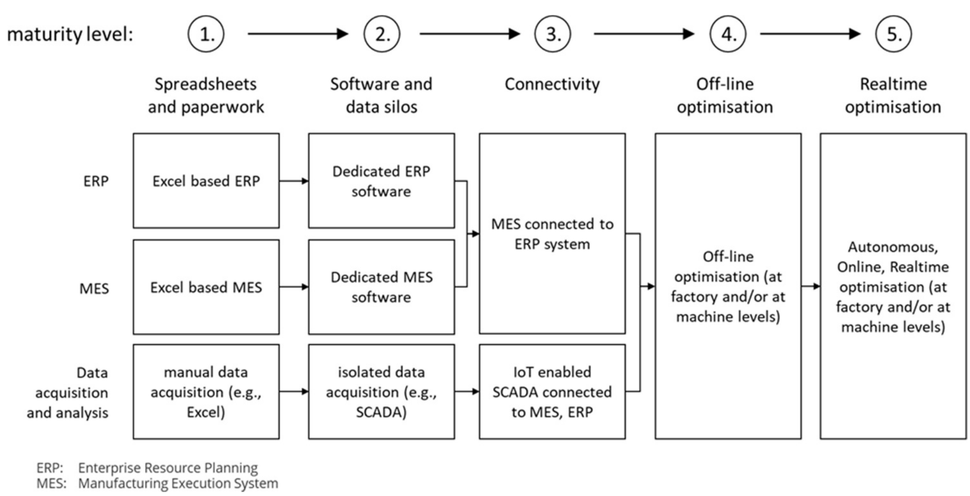

Figure 5. Autonomous & Smart Factories (EFFRA, 2020) pathway for the digital transformation of processes (Autonomous & Smart Factories Pathway, n.d.).

Table 1. Maturity levels for autonomy.

ID	Description
Level 0	No autonomy: humans have full control without any assistance.
Level 1	Assistance concerning select functions: humans have full responsibility and make all decisions.
Level 2	With partial autonomy in clearly defined areas, humans have full responsibility and define goals.
Level 3	Delimited autonomy in larger subareas, the system warns if problems occur, and humans confirm solutions recommended by the system or function at a fall-back level.
Level 4	The system functions autonomously and adaptively; humans can supervise or intervene in emergencies.
Level 5	Humans need not be present for autonomous operations in all areas, including cooperation and fluctuating system boundaries.

and cybersecurity. According to these pathways and the Platform Industrie 4.0 ("Plattform Industrie 4.0", 2021), the following levels can be defined for autonomy regarding AI in industrial production. The intervention points for applying the AI dimension in the CCMS2.0e model had been aligned to the maturity levels (see Table 1).

The practical alignment of intervention points of the AI dimension and the autonomy/development levels are discussed in the use cases (Section 4). The description of AI implementations of actual companies represents the connection of the AI dimension's five aspects. The maturity levels can be defined separately for each aspect. The overall autonomy level of a company is defined as the highest autonomy level of all aspects, determining the technical culture of the company. This technical culture should motivate the company to raise the lower levels, resulting in continuous development.

2.5. Approach to extending CCMS 2.0

Maturity models have a vast amount of literature. Still, there is no uniform approach because the suggested framework must be more specific and tailored to the application and the subject to be measured. 'Readiness' and 'maturity' are often used interchangeably in the literature. A readiness assessment usually aims to identify risks, opportunities, potential challenges, and barriers to success (Pirola et al., 2019). Becker et al. (2009) argue that maturity and readiness assessment models aim to evaluate a company's position objectively. 4IR maturity models provide guidelines and enabling frameworks as benchmarks enriched with improvement steps. Assessing 4IR maturity levels reveals a company's status and position in this roadmap with a protocol of progression through stages. It enables continuous improvement and supports comparing the company with its competitors. There are several 4IR readiness evaluation methods and maturity models in the literature (Bertolini et al., 2019; Castelo-Branco et al., 2019; Mittal et al., 2018) concerning the identified aspects (Table 2); however, according to our investigation, they do not adequately emphasise the AI aspects.

Teichert (2019) proposes a six-step approach for developing a digital transformation maturity model in service organisations: (1) defining scope, (2) designing, (3) populating, (4) testing, (5) deploying, and (6) maintaining. This approach was applied in the development process of the CCMS2.0 model. Companies already tested this, and their feedback was incorporated into the evolution of the model.

Table 2. Key differences in 4IR maturity models.

Aspect	• Different approaches and evaluations
Method	• Self-assessment • On-site audit • Workshops+ • Self-assessment
Aim	• Obtain a single global view of a company • Obtain multiple views from different perspectives on a company
Scope	• Local resources • Strategy • Real-world • Virtual world • Human • Products & Services • Value chain
Evaluation strategy	• One respondent represents the entire company • Multiple respondents are aggregated
Developer's priority	• Continuous data collection to enlarge the knowledge base, and provide a common benchmark • Continuous data collection to enlarge knowledgebase, and earn money based on this. • One-time data collection to enlarge the knowledge base • Earn money based on temporarily collected data • No knowledge base building
Approach	• Scientific • Business (€)
Dimensions/ Questions	• Number of dimensions • Number of questions

The authors use the same for the model extension (Nick et al., 2019). The extended model was tested and evaluated for the additional dimension through four use cases.

3. CCMS2.0e and its predecessors

The CCMS model (Nick et al., 2020) and the CCMS2.0 (Nick et al., 2021) are implemented as an online survey tool considering business and technological views. The model evaluates 4IR maturity on seven dimensions: 1) the Physical world, the plant and equipment of the supply chain that is fitted with cyber-physical systems; 2) the Virtual world, the 'digital twin' of the Physical world that is used to automate, remote control, optimize, and simulate the operation, 3) the Human dimension: the People who can exploit the possibilities of 4IR, 4) the Products and services: their digital content and how it is integrated to the ecosystems, 5) the Value chain: how joint systems enable to create a virtual world, 6) the Environment: how the local resources surrounding the business form an ecosystem, that collectively contribute to business competitiveness, and 7) the Strategy and culture: that acknowledge that competitiveness relies on exploiting the opportunities of 4IR. There are five intervention points connected to each dimension of the CCMS2.0 defining those actions that would increase the maturity. An example for the intervention points, using the dimension: Virtual world could be the following: a) Data acquisition and storage enabling automatic processing, b) Data exploitation in process improvement and decision support, c) Digital twins to enable connected and autonomous process execution, d) Automated, intelligent processes that can adapt to the changes of their environment and the e) Security awareness of the company. The survey questions are connected to one or multiple intervention points, probing the maturity level of the respondent's business on the seven dimensions. The model's output (in addition to the statistical evaluation of the results, is a list of intervention points that shows the respondent's most important fields of action on an interactive dashboard. CCMS provides a quick (meaning that the respondent gets prompt results), low-risk, online maturity assessment for organisations.

3.1. New dimension: Application of AI

Although certain AI-related aspects have already been embedded in the existing CCMS2.0 maturity model (Nick et al., 2021), the need for a separate AI dimension was recognised due to the importance of this field. This need was reinforced by the research of Hizam-Hanafiah et al. (2020), who investigated 4IR maturity models by analysing 30 from academia and industry, covering 158 unique dimensions. They found that the models are mainly technology-focused; 70 (44%) dimensions are related to a specific technology, concluding that organisations must focus on their technology readiness to improve their 4IR maturity. Expert interviews showed the same results: decision-makers mainly focus on developing and implementing technologies, such as AI solutions, to 'be 4IR'. Our interviews aligned with the literature review, namely, that the extensive application of AI methods in practice is still low; however, the number of pilot projects and test use cases is increasing. Using the literature review results and expert interviews, the CCMS2.0e model (Figure 6) was created with an additional dimension called the *Application of AI*. This new dimension, like the existing ones, includes five intervention points. These intervention points are underpinned by the results of our literature review,

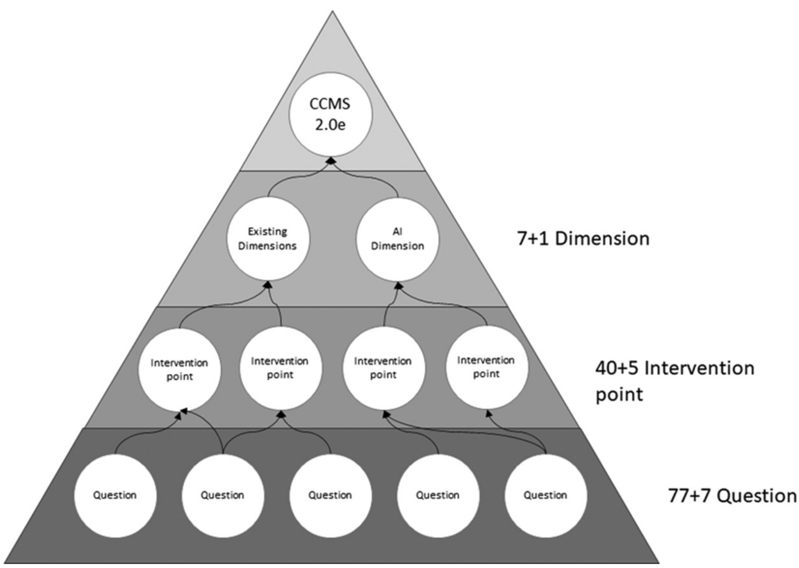

Figure 6. Structure of the updated CCMS 2.0e model.

Table 3. Aspects and key scientific references for AI dimension.

Intervention points	Key points	Relevant scientific references
Awareness of the company	Separate organisational unit and dedicated financial resources focusing on AI	Barykin et al. (2021); Cunbo et al. (2018); Fei et al. (2018); Liu et al. (2020); Tao and Zhang (2017)
Value chain	AI is used to communicate with customers and work with supply chain partners	Alcaraz and Lopez (2022); Barykin et al. (2021); Cozmiuc and Petrisor (2018); Greif et al. (2020); Kuehn (2018); Moyne and Iskandar (2017); Rymarczyk (2020)
Equipment	Equipment is fitted with AI components with the aim of autonomous operation	Malik et al. (2022); Moyne and Iskandar (2017); Longo et al. (2019); Talkhestani et al. (2019);Tao and Zhang (2017); Qi and Tao (2018)
Virtual processes	Digital twins are utilised to support management decisions through planning, simulation and optimisation	Castañé et al. (2023); Fei et al. (2018); Liu et al. (2020); Longo et al. (2019); Rathore et al. (2021); Talkhestani et al. (2019); Qi and Tao (2018)
Products and services	AI is embedded in the products to support maintenance, troubleshooting, and future product development	Fei et al. (2018); Kamble et al. (2022); Lee et al. (2020); Liu et al. (2020); Min et al. (2019); Qi and Tao (2018); Zhang et al. (2020)

shown in Table 3. Existing questions about AI have been restructured to the new dimension and intervention points.

Technically, the model is constructed from the bottom up. The examination of responses to questions influences the values assigned to their corresponding intervention points. The impact of a question may extend to the values of multiple intervention points. These intervention points are organized into higher-level dimensions, forming a comprehensive overview of the identified maturity within the respective dimension.

AI awareness of the company intervention point suggests that the company should operate a separate organisational unit to ensure the continuous operation, update and development of AI technologies based on the Responsible AI (RAI) approach, considering ethical aspects too (Mezgár & Váncza, 2022). It should continuously monitor the range of new areas AI can support (according to expert interviews, a separate organisational unit is a strong facilitator of AI development). In addition, special financial resources should be allocated to developing and applying new, cutting-edge technologies utilising AI. The importance and the role of AI should also be communicated to the employees.

AI in the value chain intervention point suggests that the company should reach out to and communicate with the customers and supply chain partners through AI-supported digital platforms that eventually synchronise the value chain autonomously. It also advises that customer needs should be analysed and assessed utilising AI technologies.

AI in the equipment intervention point suggests that it should be fitted with or include AI components that can eventually autonomously operate it or initiate maintenance and optimise the value-creating processes. Autonomous operation means that no continuous physical presence of the human is required. For example, movement coordinates could be analysed with AI or AI-enhanced fault detection could deliver value through scrap reduction, quality improvement, and optimised equipment maintenance (Moyne & Iskandar, 2017).

AI in virtual processes intervention point suggests that AI-enabled digital twins should be developed and leveraged throughout the value chain to support management decisions and to run business processes autonomously. This could include AI-enabled forecasting, planning, simulation, and optimisation based on data analysis and modelling. For example, material flow on the shop floor is modelled with a digital twin, and the assignment of shipment location is performed automatically to optimise the logistics network. AI can also deliver added value by lowering the cost of maintenance operations by optimising maintenance activities and reducing spare parts stockholding (Longo et al., 2019).

AI in products and services intervention point suggests that data should be generated during manufacturing and throughout the product's life and processed and utilised using AI technologies. These results should be used in the product design, development, production, and testing processes, as well as in troubleshooting and maintenance. Zhang et al. (2020) suggested a deep learning-enabled framework for intelligent process planning towards digital twin manufacturing cells (DTMCs). DTMC is an integrated multiphysics, multiscale, probabilistic simulation model of a manufacturing cell (Zhang et al., 2019, 2020; Zhou et al., 2020).

4. Discussion

This section discusses the use cases of the new AI dimension of CCMS2.0e. The maturity assessment model was tested on four medium-sized enterprises, or units of multinational enterprises, engaged in manufacturing. They were selected as AI should be relevant for them from a value creation point of view: human and machine interaction would play a crucial part in their value chain; they are integrated into larger supply chains where virtual processes with suppliers and customers could be complex, and their products would include AI components. After a brief introduction of the company, each AI dimensional assessment is summarised for all four cases. An overall assessment of the cases is provided at the end of the section with the learnings of using the new AI dimension.

4.1. First case – SME in the field of environmental protection

The SME is operating in environmental protection; they are engaged in recycling metal beverage cans. According to the regulation, a deposit refund system for beverage containers will be mandatory in the EU (from 2025), including Hungary (from 2024), which underlies the importance of the SME's services. They develop, maintain, distribute, and operate reverse vending machines that collect aluminium cans for reprocessing.

4.1.1. AI in general

AI is strategically important for SMEs, especially in the context of embedded components of the reverse vending machines and the services they render. They develop and use AI solutions, such as machine learning, image, material and visual shape recognition for beverage cans collection. They also utilise built-in AI solutions in camera-based recognition systems. They are convinced that AI-related competencies are required in their field, which is becoming more of a core competence. In the future, they plan to utilise additional AI solutions in their operations, e.g. logistics. They have R&D projects in AI in image, shape, and object recognition; they develop their ML solutions for reverse vending machines. ML and AI solutions support fraud detection as well. Some of their suppliers apply embedded AI solutions in camera systems.

4.1.2. AI awareness of the company

There is no dedicated organisational unit nor financial resources for AI development; however, employees work on AI/ML solution development, which is an essential competency. Regarding the ethical issues related to AI, they do not process personal data; the issues are mainly related to fraud detection. Customers' potential fraud is closely linked to the false acceptance rate (FAR) and the false rejection rate (FRR) of object recognition; therefore, meeting industry requirements is crucial.

4.1.3. Value chain

Communication and cooperation with business partners happen solely on digital platforms. This includes the development of machines, where the announcement of tenders and calls and the communication with engineering during machine build are digital. Forecasting is essential in reverse vending machines' operations, such as planning their emptying and maintenance. Statistical models have been used mainly, and an AI-based forecasting pilot is planned for 2023. Forecasting is and will be applied as a decision support system, a human decision-maker to select from the proposed alternatives and initiate the activity. No autonomy of algorithms is planned soon. Customer behaviour is analysed by AI methods using machine logs; it is mainly used to plan maintenance activities. Suppliers' data are not investigated, and it is not planned to do so. Social media sources are irrelevant; customer complaints are centrally managed, or the machine operation/management team reports them.

4.1.4. AI in the equipment

Can collection run autonomously, embedded AI is a crucial part of the machines, e.g. machine vision, robots, and data processing systems. The machine assembly process does not apply AI; it is a manual process except for the chip installation, which is an SMT (surface-mount technology). The company plans to use robots in their operations for material handling.

4.1.5. Virtual processes

There are two main business processes: making reverse vending machines and managing the logistics of collected aluminium cans. There is no AI support for the first one. The process is human-controlled in logistics, and a digital twin is planned to be developed for the logistics network, including rule-based simulation to support forecasting and planning.

4.1.6. Product and services

The service that the business renders have a strong AI-enabled digital component. Every transaction is logged, stored in the cloud, and used for logistics and maintenance planning.

The estimated AI maturity level using CCMS2.0e: 3. While the core processes of the enterprise, operating the reverse vending machines, is broadly autonomous, their logistic network planning and operation are still human-centred. The maturity assessment highlighted opportunities for the business to benefit from the pervasive use of AI, leveraging virtual processes and digital twins in the value chain. This would, however, require a more focused effort, dedicating resources and funds to developing and executing projects in this field.

4.2. Second case – multinational automotive firm

The factory is part of a global automotive parts manufacturer that has multiple operations in central Europe. The company produces electrical components by injection moulding plastic parts and assembling them with other components. The company applies lean manufacturing processes and advanced data analytics techniques, developing a leading position among its regional peers. The Digital Factory Site Leader who was interviewed oversees the technical development function of the factory but also plays a regional role in digitisation.

4.2.1. AI in general

The company recognises AI as a source of competitive advantage. There is a dedicated function at the group level, and several AI-related projects are being implemented.

4.2.2. AI awareness of the company

Although AI does not appear as a separate item on the factory's strategy, several performance improvement projects have been implemented utilising AI. Both external and internal resources and know-how are used for these projects, covering anomaly detection for mechatronic devices, predictive maintenance, or process optimisation. While no dedicated organisational unit or personnel is dealing with AI strategy and implementation, a person is being developed to lead the region's efforts in this field. The difficulty of having technical domain knowledge and the necessary programming, statistical and machine learning – artificial intelligence skills of the subject matter expert was mentioned repeatedly. As subject matter experts are difficult to find, they try to develop these skills internally. As AI projects are often data-intensive, the need to have a data infrastructure was highlighted. The factory invested heavily in this field during the previous years; therefore, data acquisition and storage are less of an obstacle for AI initiatives now. Ethical issues related to AI have not received focus.

4.2.3. Value chain

Communications with business partners are performed entirely using dedicated digital channels. Forecasting and production scheduling processes use AI methods; however, the final decision is performed by humans. Due to recent supply network disturbances (e.g. the COVID pandemic), these processes had to be developed using more sophisticated AI-based methods to cope with the new requirements. The use of social media networks as a source of information has not emerged, as the factory does not service consumers directly.

4.2.4. AI in the equipment

Manufacturing equipment runs autonomously, often including AI-enabled parts, e.g. computer vision with embedded AI is used for automated quality control. The data that is generated by the equipment's sensors is analysed locally. There have been recent efforts to develop an AI-enabled anomaly detection function with definitive diagnostic capabilities that could be added to existing equipment for the early identification of malfunctions or maintenance problems.

4.2.5. Virtual processes

Digital twins exist for all levels of manufacturing, from products, tools and equipment through plant layout and the supply chain. Process improvement and management utilises AI-based methods and solutions; however, processes are not run autonomously.

4.2.6. Product and services

Due to the nature of the factory's product portfolio, thus far, there have been limited opportunities to include AI components in the products. More complex products include sensors communicating with the host system's AI-related components. In the future, the product portfolio may be extended with products that consist of complex AI components.

The estimated AI maturity level using CCMS2.0e: 3. The manufacturing equipment runs autonomously, and digital twins exist at multiple levels; however, value chain processes still require significant human intervention. The maturity assessment highlighted the difficulties of transforming a manufacturing process with islands of autonomous operations and pockets of embedded AI components to integrated, autonomous operations. It would require new skills and the development of autonomous value chain processes.

4.3. Third case – multinational company in the field of manufacturing

The multinational company was founded in Eastern Hungary in 2001 and has become a definitive factor in the region, being one of the largest power tool producers worldwide. The company – which employs over 3000 employees – assembles power tools, garden machines, and batteries for them; it also develops and manufactures electric bike batteries.

4.3.1. AI in general

The company applies big data analysis and machine learning methods to create safe, robust, and explainable AI solutions in manufacturing and engineering. These solutions include inter alia automated optical inspection, anomaly detection and root cause analysis. AI is planned to be used in production scheduling and supply chain cost optimisation. The company also runs R&D projects in machine learning, data analytics, and battery quality prediction.

4.3.2. AI awareness of the company

The company has a dedicated organisational unit that initiates and realises AI projects, focusing on production. A company-wide Data Steward Network is being established to recognise that supporting the increasing AI activities from one central unit is almost impossible. The plan is that each organisational unit must have at least one Data Steward, who shall be familiar with the department's processes and can launch and support data analytics projects to accelerate the efficient usage of AI in all business segments.

4.3.3. Value chain

Value chain processes, including manufacturing, engineering, logistics, purchasing, and finance, are digitalised. Production planning does not use AI technologies as the input data (orders) is not yet prepared. Value chain synchronisation, forecasting and planning are still human-centred.

4.3.4. AI in the equipment

Most workstations require human operators; however, they have MES connections, so machine and process data are collected and transferred to the cloud. A scalable AI and analytics solution helps with big data visualisation, root cause analysis and anomaly detection. In addition, embedded AI is used in the production of robots and machine vision. The battery production uses patented servo welding heads that measure all welding parameters (e.g. voltage, current, force) in real time. This data is processed with machine learning methods using clustering, classification, and regression to predict the tensile strength of all cell welding points, guaranteeing the quality of battery packs.

4.3.5. Virtual processes

The company has developed its production support system, where relevant production and logistics process information is stored and processed in real time. The system functionality is between Level 2 and Level 4 on the ISA-95 standard reference model, equivalent to MES functionality. This system acts as the digital twin of manufacturing and intralogistics; it has delimited autonomy and is used actively for simulation and optimisation. The system using the digital twin can predict the start of the next production lot, order material from the warehouse automatically, and even cancel transport orders in case of any issues.

4.3.6. Product and services

A cloud-based platform ensures that all relevant data about the products and services is available, such as ordering, packaging and shipment information, manufacturing and parts traceability, warranty, and after-sales information. This data carries valuable knowledge throughout the lifecycle of products. The platform also works as a customer portal, with convenient access to numerous services.

The estimated AI maturity level using CCMS2.0e: 3. The production support system operates with delimited autonomy, and human assembly operation is supported extensively with data collection and analysis. The maturity assessment reinforced the importance of local resources for developing AI applications. It also showed that while autonomy has been achieved at lower levels of manufacturing operations, there are opportunities for leveraging AI for synchronising the value chain.

4.4. Fourth case – a multinational company in the field of automotive electronics

The factory, which was established in 1998, is the largest manufacturing centre of a multinational company's automotive electronics division. It employs more than 5,300 employees. Its main products are control units for hybrid and electric cars, sensors, voltage regulators, and power steering control electronics.

4.4.1. AI in general

The company's 4IR strategy is based on four pillars: digitalisation, quality, environment, and workforce. Digitalisation is at the centre of the company's 4IR strategy; digital solutions are developed to improve production performance, e.g. automation of material handling and material flow or analysis of deviations from desired states.

4.4.2. AI awareness of the company

Recognising that external data analytics experts do not have sufficient knowledge of internal company processes, an internal analytics team has been created, initially as part-time assignments that evolved to full-time jobs. The team's goal is to improve data expertise within the company by promoting professional data visualisation and analysis. Several in-house software tools have been created to support the goal, using best-of-breed software solutions combined with in-house development.

4.4.3. Value chain

While the communication with suppliers is all digital, only the large ones use the company's platform. Smaller customers use more traditional methods like email. Demand forecasting and production planning are the main value chain processes; the former uses AI algorithms but still requires human intervention. Production lines order raw materials automatically from the warehouse, which are delivered to the lines by Automated Guided Vehicles (AGVs).

4.4.4. AI in the equipment

Data collection goes back some 15 years when almost all set and measured parameters related to the production of a given product could be retrieved. The main use of this data is related to quality assurance. Production line performance is monitored automatically and displayed above each line in real time. AI and ML algorithms help detect manufacturing defects by considering process parameters from suppliers and customers. 'Put-by-light' technology is also used in several stations: automated visualisation assists the worker, showing him the right box when preparing the raw material. Materials in production sometimes use various sensor solutions to help with positioning. Automated Guided Vehicles (AGVs) transport raw materials from the smart supermarket to a defined storage point directly to the ERP system with automatic feedback via RFID readers.

4.4.5. Virtual processes

Line simulation models are mainly used as virtual processes. It is used during the design phase to validate line design or for line capacity extensions to evaluate different scenarios. It is also used for operational purposes, e.g. determining a product mix's line control strategy.

4.4.6. Product and services

Approximately 200 billion production and product test parameters are collected and stored daily. PLCs of the machines automatically send the relevant process parameters to these databases. This data is stored online for three years and archived for 15 years.

The estimated AI maturity level using CCMS2.0e: 2. While data collection is expansive in the company, AI is used only sporadically in clearly defined areas. The maturity assessment highlighted that data collection, analysis and performance monitoring are insufficient to move towards autonomous operations that benefit from AI. Assessing the long-term business benefits of AI and capturing these opportunities would require dedicated resources whose skills and mandate would be far beyond data analytics.

4.5. Overview of the cases

The interviews to test the extended CCMS2.0e maturity model using the five AI-related intervention points highlighted the following:

- All four companies recognised the importance of digitisation and AI. However, none of the companies created an AI strategy and established an organisational unit with dedicated funds to drive the development and pervasive implementation of AI technologies in the business. A potential skill gap of experts that requires both domain and AI knowledge was also identified. This gap will likely be closed by equipping internal resources with AI knowledge. Ethical and responsible AI issues are not the companies' focus.
- Value chain synchronisation using AI solutions is far from being autonomous. Communication with suppliers and customers is mostly digital but usually requires human intervention.
- At the equipment level, the highest levels of AI-enabled autonomy. In most cases, they can operate with minimal human intervention using embedded AI solutions.
- The development of virtual processes and the digital twins is the bottleneck of creating autonomy in running production, manufacturing, and logistics. While certain models, virtual processes and digital twins exist and are used for offline simulation and optimisation, they are far from autonomous.
- The level of digitisation of products and services is very much dependent on the nature of the products the companies produce or the services they render. While data is collected extensively during the production phase of the product, data collection during the product's lifecycle varies.

The summative insights from the cases offer valuable contributions to theoretical understanding and practical applications. The model developed in this study endeavours to encompass various dimensions, including AI and articulate questions that facilitate the assessment of maturity within these dimensions at the company or business unit level. Theoretically, the model extends the conceptual grasp of organizational maturity, providing a structured framework for analysis. This theoretical contribution enhances comprehending and studying the intricate dynamics of maturity within organizational contexts. On a practical level, the model serves as a tool that consultants can employ to evaluate maturity and establish development directions for companies or business units. Its applicability in practice is a valuable resource for consultants seeking to make informed assessments and guide strategic development initiatives within organizational settings.

5. Conclusion

This paper presented the extension of the CCMS2.0 maturity model, covering the aspects of AI. Literature review and expert interviews from manufacturing companies defined a new, AI-related dimension of the CCMS2.0 maturity model, including intervention points. The literature review has shown the growing importance of AI in the field of 4IR, with an increasing number of publications covering both theoretical models and practical applications. Deep learning was the most popular AI method, followed by classification and reinforcement learning. While digital twins should be important elements of AI in intelligent manufacturing, providing the virtual representation of the physical assets, our text analysis of the literature has yet to confirm this. The most important concepts in the literature on AI and digital twins in manufacturing, production and logistics were the Internet of things, the cyber-physical system and simulation algorithms, optimisation, and prediction. The concept of digital twins was only weakly connected to these.

The analysis of the existing 4IR maturity models revealed that they do not cover AI aspects. While certain AI-related aspects have been embedded in the CCMS2.0 maturity model, the need for a separate AI dimension was recognised due to the importance of this field. The intervention points of this new AI-related dimension cover the awareness of the company, the value chain from an ecosystem aspect, the AI applications embedded in the equipment, the virtual processes and the AI elements of products and services. The maturity levels for this new, additional dimension range from the lowest, where humans have full control over the processes, without the assistance of AI, to the highest, AI-assisted autonomous operations, without the need for human presence. The interviews from the four industrial use cases show that several AI methods and applications are used in the companies; however, they are far from the autonomy 4IR should aim for. While AI is not necessarily elevated to create a dedicated strategy or organisational unit at the companies assessed, activities are visible in their value chain areas. Projects are being implemented to leverage the potential benefits of AI. It is increasingly embedded in the equipment, performing key functions or supporting maintenance or supervision. The communication in the value chain was almost entirely digital in the cases covered, leading to the growing amount of data that could enable AI in production planning, scheduling, and simulation. AI, however, is not widespread in this area yet; it is used sporadically or only for pilot projects. The virtual processes, the digital twin, is the weakest link to achieving autonomy. More effort should be given to understanding how AI could lead to achieving autonomous operation. AI in the products and services depends greatly on the company's portfolio. Data collection during production is prevalent and is analysed extensively using AI methods. The AI components of products and services are less developed, and developments are expected in this area. The cases highlighted the importance of AI in manufacturing; companies want to keep abreast with the developments in this area, making the addition of the AI dimension of the CCMS model relevant.

This scientific research provides an example of how AI could be included in the 4IR maturity models, keeping them updated with technological advancements. The research is subject to certain limitations that merit consideration. Firstly, the study is confined to a specific geographical context, namely Hungary, which may restrict the generalizability of the findings to a broader or diverse context. The limitations extend to the data collection process, where challenges arose in accessing and selecting domain representatives. Intervention policies exacerbated these challenges, making ensuring a representative sample difficult. The CCMS2.0e model provides new research opportunities in developing 4IR maturity assessment models extended with AI dimension. Future research will include a more comprehensive validation of the proposed model, which could be achieved with a broader range of use cases. This would provide a firmer basis for generalising the results and applying them beyond the scope of the current study. Future research on the CCMS2e model should also include assessing how AI models and techniques used in companies affect carbon emissions.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

Data sharing does not apply to this article as no new data were created or analysed in this study.

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