

(REVIEW ARTICLE)



DIGITAL TWIN AGGREGATES AND BIG DATA ANALYTICS FOR PREDICTIVE RISK MANAGEMENT IN CONTINUOUS MANUFACTURING: A SYSTEMATIC LITERATURE REVIEW

Kudakwashe Marufu *, Tinashe Masvaure, Leeroy Masukume, Lovemore T. Mandebvu and Tapiwanashe Masawi

Department of Industrial and Manufacturing Engineering, National University of Science and Technology (NUST), Bulawayo, Zimbabwe.

* Corresponding Author

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ABSTRACT

Digital Twin (DT) technology is a virtual representation of a physical asset, process or system that is continuously updated from operational data and is a key enabling technology for Industry 4.0 manufacturing research (Grieves and Vickers, 2017; Kritzing et al., 2018). Most of the current studies are related to the single asset, such as condition monitoring and fault diagnosis/predictive maintenance, using DTs (Tao et al., 2019; Tekinerdogan et al., 2021; Catal et al., 2022; Chen et al., 2023). The asset-level approach is not entirely appropriate for continuous manufacturing where machines and processes are highly inter-dependent and a disturbance at one step can make it to the flow, pressure, product quality and downstream processes. A way forward from asset level to system level risk prediction is through Digital Twin Aggregates (DTAs) that integrate information from several DTs into a system level view, along with big data analytics (Lu et al., 2020). While the implementation does have challenges of data integration, computational requirements, interoperability and standardisation (Shao and Helu, 2020; Perno, Hvam and Haug, 2022), these are heightened in resource-constrained, developing industrial economies (Muhla et al., 2025a; Mashava et al., 2026). This paper is a systematic literature review (SLR), performed following the PRISMA 2020 statement (Page et al., 2021) and the guidelines provided by Kitchenham and Charters (2007). Records published between January 2016 and September 2026 were obtained from Scopus, Web of Science, IEEE Xplore and ScienceDirect and a total of 88 records were screened to identify 50 studies with an average quality score of 4.12 out of 5. All studies included were classified based on a multidimensional taxonomy of DT architecture, manufacturing level, data sources, analysis techniques, risk-management function, and validation environment. Among the 50 studies, there are 22 that are reviews or surveys, and only 19 that include empirical studies, 11 of which involve continuous or process manufacturing, and none of which have been validated with industrial data in a continuous process, in the case of multi-twin or aggregated architectures. The review summarizes existing applications, emerging technologies, and industrial implications, and identifies a research roadmap for practical, interoperable and system-level predictive risk management for continuous manufacturing.

Keywords: Digital twin; Digital twin aggregate; Big data analytics; Predictive risk management; Continuous manufacturing; Industry 4.0; Systematic literature review.

1 INTRODUCTION

The Digital Twin (DT) technology is an important aspect of the Industry 4.0 and modern manufacturing. A Digital Twin is a virtual model of a physical machine, product or system that is based on real-time data to accurately reflect its state and actions (Grieves and Vickers, 2017). Digital Twins are also employed in manufacturing to monitor production, optimise production processes, and detect and predict faults and failures (Kritzinger et al., 2018; Tao et al., 2018b). Digital Twins are of special value in continuous manufacturing where machines and processes are all integrated.

Failure in one machine can impact the other production processes leading to equipment failure, downtime, poor product quality and other operational risks. For instance, in the case of edible oil refining, an OOS bleaching stage leads to reprocessing, increasing cycle times and usage of bleaching earth, whereas in thermal power generation, in the case of a boiler failure, it means forced outage or instability in generation. The early discovery of these issues can then enhance reliability and minimize losses on the production line. There remain various challenges with Digital Twin implementation, however, including data integration, interoperability and system complexity (Perno, Hvam and Haug, 2022). They are more severe in less industrialised economies. Muhla et al. (2025a) identified some technologies under Industry 4.0 being used on the shop floor of Zimbabwe manufacturers, but due to high implementation costs and the lack of supportive policy, the shops are not optimising the use of these technologies and they are not well interconnected.

Agility is a strategic must for these companies (Muhla et al., 2023) making downtime without an agenda extremely expensive, and condition monitoring via IoT is still in its infancy for many of the African plants (Mashava et al., 2026). A system-level approach to risk is thus not only a research interest but a necessity for manufacturing companies that cannot withstand repeated disruptions. The majority of the current research is addressing individual machines, particularly predictive maintenance (van Dinter, Tekinerdogan and Catal, 2022). This may not give a comprehensive view of the evolution of risks in a connected manufacturing system.

Digital Twin Aggregates (DTAs) aim to overcome this limitation by integrating data from multiple Digital Twins to create a more comprehensive understanding of the production system. All the data generated by the sensors, IIoT devices, control systems, and maintenance records can then be analysed using big data analytics to detect any unusual conditions and potential problems. Although this approach has potential, research on system-level predictive risk management using connected Digital Twins remains limited. Therefore, this review addresses the following questions:

- **RQ1:** How are Digital Twins aggregated in continuous manufacturing?
- **RQ2:** What big data analytics techniques support predictive risk management?
- **RQ3:** What manufacturing risks can aggregated Digital Twins identify or predict?
- **RQ4:** What data sources and architectures support these systems?
- **RQ5:** What challenges and research gaps remain?

The aim of the review is to define the state of research and suggest research directions. Its product is a PRISMA-compliant and quality-appraised evidence base of 50 studies, a multidimensional taxonomy applied to each of the included studies, which distinguishes asset-level from aggregated, system-level twins, and a research agenda that considers the human, energy and resource constraints of developing industrial economies.

2 BACKGROUND AND THEORETICAL FOUNDATION

2.1 Background

The digital twin concept has its origins in an idea that made its way into the culture, which suggests that one could connect a physical product to a virtual representation using data (Grieves and Vickers, 2017). Later it evolved in the fields of product lifecycle management, manufacturing and engineering (Kritzinger et al., 2018). Research differentiates digital models, digital shadows and digital twins based on the link between the physical system and the digital representation. Digital Twins can aid in manufacturing production management, equipment monitoring, maintenance and process improvement.

However, some systems do not offer full services to physical assets or consistently feed back analytical results to the real system (Tao et al., 2019). Production lines are made up of various pieces of equipment which have links to each other, if one of the equipment fails, it has an impact on other equipment. Digital twin aggregation is thus pertinent for integration of multiple representations and for big data and system level risk analysis. The ability to build the competency to design, integrate and maintain these systems is another constraint. Learning factories, which afford learners a real-life production environment for experiential learning and applied research, are also used to support Industry 4.0 and digital twin education, although only in South Africa in Southern Africa to date, with a lack of skills in

IoT, automation, AI and big data (Ndiyamba et al., 2026). This is important for this review as the learning factories also offer low-risk settings where aggregated twins can be prototyped and validated before planting in the field.

2.2 Theoretical Foundation

2.2.1 Digital Twin Theory

The concept of digital twin theory is based on the interplay between physical objects, their virtual twin and the information that is exchanged between them (Grieves and Vickers, 2017). It is useful for applications such as products, manufacturing systems, simulation, data management and intelligent decision-making (Lu et al., 2020).

Implementation maturity can be assessed with the classification of digital models, digital shadows and digital twins (Kritzinger et al., 2018). A digital model can be used without automatic data exchange, a digital shadow is based on the physical system and receives data, and a digital twin allows for a more comprehensive data exchange between the physical system and the digital shadow. Digital twins should be built to the purpose, and based on available data and operational needs. A structured implementation, composability and reusability, suitable data selection and scope definition are also highlighted in manufacturing frameworks (Shao and Helu, 2020).

2.2.2 Digital Twin Aggregation and System-of-Systems Theory

Digital twin aggregation is the process of putting together multiple digital representations in a connected, system-level context. This is in the context of System-of-Systems thinking, which consists of a collection of systems that interact with each other and operate somewhat independently. For instance, in a bakery, the separation of the twins could be the various mixers, ovens, motors and conveyors and the aggregation of the twins could represent the relationships between all the production process components.

In the case of an aggregation, the lower-level twins can send information to the higher-level aggregate twins in a twin-to-twin interaction, in which the existence of the interaction is explicit in the reference architectures, such as the six-layer architecture (Kruger and Basson, 2020; Redelinghuys, 2020). Computational requirements, multi-sourced data and the complexity of models are challenges of predictive maintenance using digital-twin approach (van Dinter, Tekinerdogan and Catal, 2022). A component-level twin can display a state of one asset while an aggregated twin can display a state of how the state of that asset impacts overall production. To achieve effective aggregation, therefore, one needs reliable data, valid models, and system integration and information exchange, not just a collection of the visual models. Multi-agent systems (MAS) provide an alternative agent-based way to achieve this.

In the copper cable manufacturing plant, four agents (diagnosis, decision, database and notification) collaborated with each other to process the data of infrared temperature sensors, electromagnetic flow meters, conductivity transducers, and a linear float sensor, and identified refractory overheating, cooling-water flow degradation, and water-conductivity anomalies on a hardware-in-the-loop testbed (Mashava et al., 2026). While this framework only tracks one asset, the separation of monitoring into independent, communicating entities has a similar structure to the twin-to-twin interaction required by aggregation, and thus the holonic and agent-based architectures are a natural implementation vehicle for DTAs.

2.2.3 Big Data Analytics Theory

Big data analytics analyzes information collected from sensors, machine controllers, production logs, quality checks and maintenance. It can be used to discover patterns, detect deviations, and make predictions regarding the behaviour of equipment and processes. Digital twins and big data complement each other: digital twins link physical assets with virtual models and analytics helps analyze the data generated by these systems (Qi and Tao, 2018). Data analysis, machine learning, anomaly detection and predictive modelling are examples of methods that can be used for predictive risk management.

They rely on the quality of the data as missing values, measurement errors, varying condition and the lack of failure records can limit the accuracy of the predictions. Therefore data validation and appropriateness of analytical approaches need to be taken into account. If failure records are rare, like those of plants that have traditionally performed reactive maintenance, there are two sources of predictive knowledge that can be used with each other. The first is machine learning on long operational histories: A Random Forest classifier, trained on 13 years of monthly boiler data from a coal-fired power station, determined the optimum reliability point for preventive maintenance and was tested against 16 weeks of new operational data, where corrective maintenance still comprised approximately 72% of the maintenance mix (Senda et al., 2026). The second is the application of statistical design of experiments.

Taguchi orthogonal arrays, analysis of variance (ANOVA) and grey relational analysis (GRA) have been used to quantify the contribution of the process parameters to the defects and quality responses in injection moulding (Mapindu et al.,

2026a), CNC milling (Mapindu et al., 2026b), fused deposition modelling (Mapindu et al., 2026c), welding optimization (Mapindu et al., 2026d), wood planing (Tayisepi et al., 2023) and cylinder-liner honing (Tayisepi et al., 2024), respectively, and predictive response modelling has been used to guide the design of a vacuum bleaching stage in edible oil refining (Jansen et al., 2025). Compact and physically interpretable, and easy to obtain, such parameter–response models are appropriate as a process model embedded in a twin where large historical datasets are not available.

2.2.4 Predictive Risk Management Theory

Predictive risk management: Identify and analyse the potential risk based on historical data, present situation and predictive models. In the manufacturing sector it aids in the preliminary identification of normal or abnormal equipment behavior and/or conditions that could lead to production delays. The concept of predictive maintenance is to use the data of the condition of equipment to predict its condition and to provide a warning before it fails, with key aims including remaining useful life estimation, condition prediction and fault detection (van Dinter, Tekinerdogan and Catal, 2022).

Digital twins simulate the behaviour of equipment, and the data from operation and big data analytics can reveal trends related to equipment failure risks (Chen et al., 2023). Predictive risk management also takes into account the impact that equipment conditions have on production continuity and the consequences of disruption. An upstream failure can cause less material to reach the downstream equipment for instance. The combination of digital twin aggregation and predictive analytics can therefore help with risk analysis on a system and asset level. Interconnected manufacturing systems (Lu et al., 2020) can be studied based upon reference models that include information modelling, data processing and industrial communication. Risk in manufacturing isn't just technical.

HFE interventions, specifically ergonomic design, and operator training and safety culture have been proven to effect a reduction in workplace accidents in manufacturing in Zimbabwe (Muhla et al., 2025b), while wearable support like a passive, upper limb exoskeleton can help reduce fatigue that causes workers to drop loads during prolonged overhead activities (Tandi et al., 2025). Therefore, operator state is a valid input for predictive risk models and a system-level twin without the consideration of the human element will miss an important cause of disruption and harm (Bevilacqua et al., 2020; Zio and Miqueles, 2024).

3 METHODOLOGY AND SEARCH STRATEGY

3.1 Review protocol

This review is carried out using a pre-specified protocol that incorporates elements of the systematic literature review (SLR) process for engineering and technical fields laid out by Kitchenham and Charters (2007) and the PRISMA 2020 reporting guideline (Page et al., 2021). The protocol was developed and consensus reached on by all the authors prior to the beginning of the search process, following Kitchenham and Charters (2007), and included the research questions (Section 1), the databases and search strings (Section 3.2), inclusion and exclusion criteria (Section 3.4), quality assessment checklist (Section 3.6), and data extraction form (Section 3.7). The key way in which PRISMA and Kitchenham and Charters (2007) attempt to reduce selection bias in a review is to fix these elements before screening.

3.2 Databases and search strings

To ensure the review team a balance between discipline coverage and access to relevant material, four databases were chosen – Scopus (broadest multidisciplinary engineering coverage), Web of Science (high impact indexed journals), IEEE Xplore (essential for CAD/CAM, control and Industry 4.0 literature) and ScienceDirect (Elsevier journals including Journal of Manufacturing Systems, Computers in Industry and Information Sciences). Google Scholar was used as a secondary source to check grey literature and recently published literature when this was not yet indexed; these are reported as ‘other sources’ in Figure 1.

3.3 Search period

Searches covered the period from 1 January 2016 to 19 September 2026. A maximum of five pre-2016 seminal sources was permitted to provide historical and foundational context.

3.4 Inclusion and exclusion criteria

Included: peer-reviewed journal articles and conference proceedings addressing digital twins, digital twin aggregates, or big data analytics applied to manufacturing or process-industry risk management.

- Included: studies published 2016–2026, in English, with accessible full text.

- Excluded: studies focused solely on digital twins for design/CAD visualization with no risk or predictive-analytics component.
- Excluded: non-peer-reviewed blog or vendor marketing content, except where it is used briefly for industry context and clearly marked as such.
- Excluded: duplicate records and studies for which only an abstract was available.

3.5 Screening procedure

A 2-stage PRISMA process was followed to screen. The database searches yielded 77 results and supplementary searching yielded 11 additional results for a total of 88 records, of which 4 were eliminated prior to screening. Stage 1 involved identification of 20 records out of the remaining 84 that were excluded based on the inclusion/exclusion criteria for the titles and abstracts. During the Stage 2, for the 64 records, full texts were not available for 12 records, and of the 52 records retrieved, two were excluded because they were irrelevant, and 50 studies were included for quality assessment, data extraction and synthesis (Figure 1).

3.6 Quality assessment

The remaining full-text records from Stage 2 screening were evaluated with a 5-criterion checklist (see Table 1) inspired by the method of Kitchenham and Charters (2007) for the quality-assessment approach on SLRs and the guidelines for systematic mapping presented by Petersen, Vakkalanka and Kuzniarz (2015). The criteria were each given a score of either 0 (not met), 0.5 (partially met) or 1 (fully met) for a maximum score of 5. All 50 of the included studies reported scores (Table 2).

Table 1: Quality assessment criteria applied to the full-text studies

Code	Quality assessment criterion
QA1	Are the aims, research questions or scope of the study clearly stated?
QA2	Is the digital twin, analytics or risk-management approach described in sufficient detail to be understood and reproduced?
QA3	Is the evidence rigorous, that is, validated with simulation, pilot or industrial data for primary studies, or obtained through a systematic and reproducible method for reviews?
QA4	Is the study directly relevant to risk, maintenance, reliability or process performance in manufacturing or the process industries?
QA5	Are the limitations, assumptions and implications for practice or further research discussed?

3.7 Data extraction and synthesis

The included studies were extracted by filling in a standardised extraction form, which describes bibliographic information, a standardisation of the type of study (review, conceptual or framework, empirical), the digital twin architecture (model, integration, processing), the level of aggregation, the manufacturing context (discrete, continuous or process, generic), data sources and analytical techniques, the risk-management function and the validation environment. These fields also reflect the dimensions of the taxonomy in Section 4, so that the data extracted from these fields could be coded directly (Table 4). Due to the methodological diversity of the studies included, no meta-analyses were conducted and synthesis of the data was performed rather by narrative methods and by frequencies.

3.8 PRISMA flow diagram

Figure 1 shows the PRISMA 2020 flow diagram (Page et al., 2021).

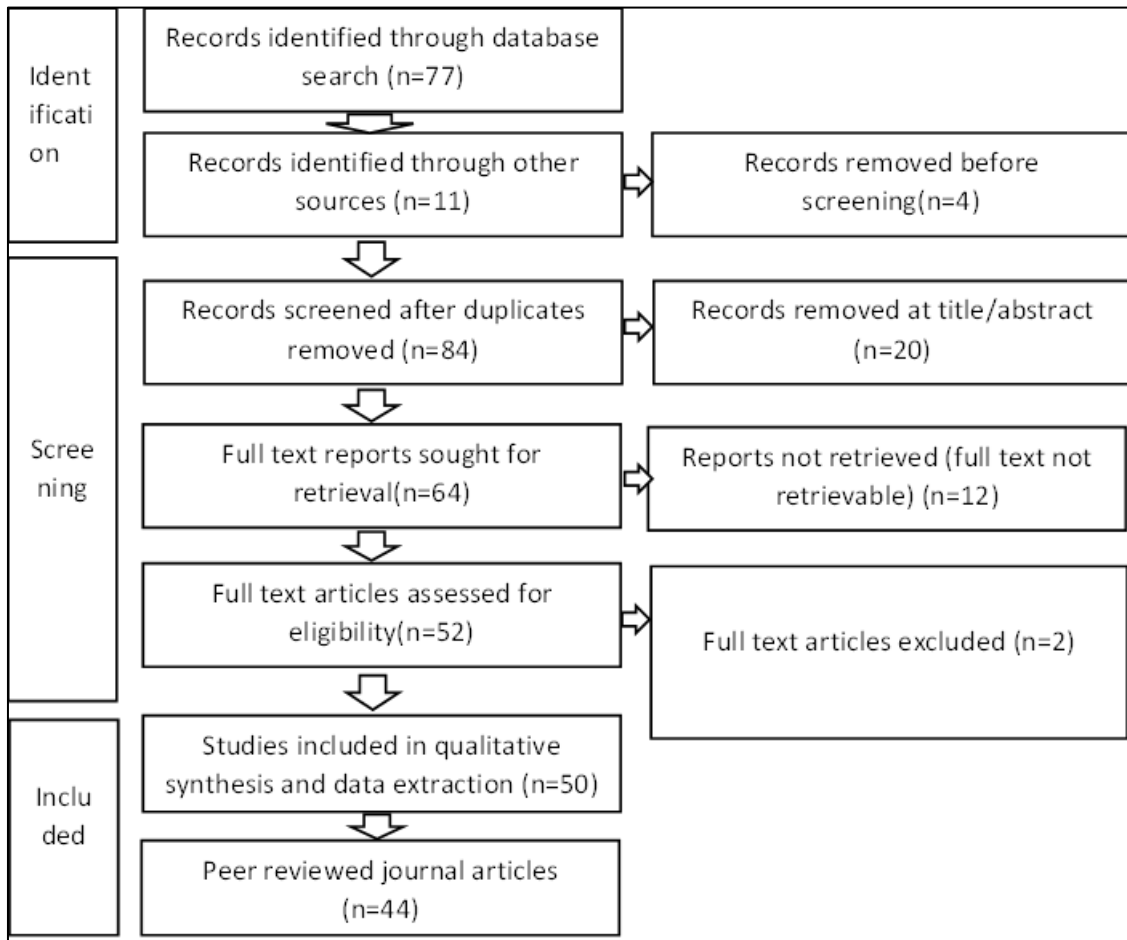


Figure 1: PRISMA 2020 flow diagram of study identification, screening and inclusion (searches run 1 January 2016 – 19 September 2026 across Scopus, Web of Science, IEEE Xplore and ScienceDirect). Adapted from the PRISMA 2020 flow diagram template (Page et al., 2021).

4 CLASSIFICATION AND TAXONOMY

4.1 Taxonomy framework

A multidimensional taxonomy of the literature, consisting of digital-twin architecture, manufacturing level, data sources, analytics, risk-management function, and validation environment, is presented. This encompasses the need to discriminate between individual twin and system-level representations. There is also a review of manufacturing DTs that performs a comparison of DT architectures, services, content, level of deployment, and level of application (Ditzel et al., 2020; Atalay et al., 2022). The dimensions and their categories are summarised in Table 2.

Table 2: Classification framework used to code the included studies

Dimension	Classification
Digital twin architecture	Individual; multi-twin; aggregated; hierarchical; system-of-systems
Manufacturing level	Component; machine; process; production line; plant; system
Data sources	Sensors/IoT; PLC/SCADA; MES; ERP; maintenance; quality; historical production
Analytics	Statistics; machine learning; deep learning; anomaly detection; predictive modelling; hybrid

Risk function	Monitoring; anomaly detection; diagnosis; failure prediction; RUL; predictive maintenance; process-risk prediction
Risk category	Equipment failure; process deviation; quality failure; downtime; production interruption; energy and utility supply disruption; operator safety
Validation	Simulation; laboratory, learning factory or hardware-in-the-loop testbed; pilot plant; industrial case study; real-time deployment

4.2 Classification by digital twin architecture

Individual digital twins are digital representations of a specific physical asset (e.g., a machine, motor or pump), typically for use in condition monitoring or maintenance. Multi-twin architectures are used to link multiple individual twins together. The aggregated digital twins aggregate information from several twins to conduct system-level analysis. Hierarchical architectures are those in which twins are organized across levels, e.g. component, machine, process, production line, plant. System of systems approaches view inter-connected systems as part of a larger manufacturing system. Agent-based implementations are based on agent interactions between cooperating software agents, monitoring and reasoning about assets (Mashava et al., 2026), are coded at the level at which the agents exchange state information. Integrating virtual entities has been recognised as an ongoing issue in digital-twin research (Jones et al., 2020).

4.3 Classification by manufacturing level and data

Studies are grouped at the component and machine level up to the process, production-line, plant and system levels. The review can then assess if research is focused on assets or moving towards the development of digital twins for systems. The classification of data is based on sensors and IoT devices, PLC/SCADA systems, MES, ERP, maintenance records, quality records and historical data production. Digital twins need to be updated with data constantly or periodically as the data becomes relevant, and in industrial applications, several data sources can be integrated to form the manufacturing behaviour (Jones et al., 2020; He and Bai, 2021). In real world, the data layer consists usually of a variety of locally available data sources, such as PLC-connected temperature, flow, conductivity and level sensors available through an OPC server for furnace monitoring (Mashava et al., 2026), multi-year operating and maintenance data from a power station (Senda et al., 2026) and production log sheets for edible oil refining (Jansen et al., 2025).

4.4 Classification by big data analytics

Analytics are classified into 5 categories: statistical analysis, machine learning, deep learning, anomaly detection, predictive modelling and hybrid approaches. These techniques are useful for the interpretation of large and diverse manufacturing datasets and can be connected to digital-twin models to monitor, diagnose, and predict. The statistical methods include design-of-experiments (DOE) methods like Taguchi analysis with ANOVA and GRA, which involve explicit parameter–response relationships (Tayisepi et al., 2023; Mapindu et al., 2026a); the machine-learning methods include ensemble classifiers for maintenance planning (Senda et al., 2026), deep transfer learning for fault diagnosis (Xu et al., 2019), and knowledge-based rule inference embedded in agent platforms as a hybrid approach (Mashava et al., 2026). Industrial digital twins have been reviewed, and production and predictive-maintenance applications have been highlighted, as has been the case in previous manufacturing reviews (Aznar Lapuente et al., 2026; Semeraro et al., 2021).

4.5 Classification by predictive risk function

The risk-management aspect of it covers condition monitoring, anomaly detection, fault diagnosis, failure prediction, remaining useful life estimation, predictive maintenance, process risk prediction and production continuity risk management. The latter is especially significant for continuous manufacturing, where disruption at one stage can impact downstream manufacturing. This is because for continuous and semi-continuous processes, an out-of-specification stage may result in reprocessing and cause delay and cost downstream, so there is an explicit inclusion of quality-related process risk. Technological risks to energy supplies, as well as operator-safety risks, are also captured: Energy supplies, especially in developing economies, are often unreliable and insufficient, leading to decentralised energy generation via slipstream wind-energy harvesting (Muyambo et al., 2025), and human factors are another major cause of accidents at work (Muhla et al., 2025b). The taxonomy thus differentiates between the prediction of failure of a single asset and the prediction of consequences of an interdependent production system.

4.6 Integrated taxonomy and synthesis

The overall taxonomy is represented in Figure 2. The framework moves from the physical assets and their digital representations to the information and analytical processes used for prediction, and finally to maintenance, process-intervention and production-continuity decisions.

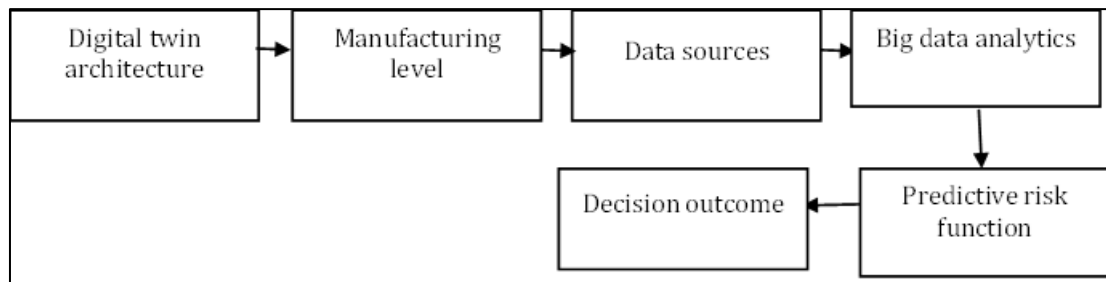


Figure 2: Integrated taxonomy linking twin architecture, data, analytics and risk-management decisions (developed by the authors)

The taxonomy provides a basis for identifying research gaps. Individual machine-level twins and predictive-maintenance studies would dominate the evidence base with few studies incorporating multiple twins over continuous production systems would signify an evidence gap in propagation of risk and continuity of production at system level. To test this expectation, every study included in this section is coded using the taxonomy.

4.7 Classification of the included studies

According to Table 4 there are three patterns. Firstly, the evidence base is dominated by secondary and conceptual studies; of the 50 studies, 22 are secondary or review/survey and another nine are conceptual frameworks or reference models, with just 19 empirical studies. Second, the validation is weak: 32 studies report no validation, four studies are based on simulation, six study a laboratory or pilot testbed, and eight studies use industrial data. Third, there is little aggregation, and it hasn't been proven in the most important setting. There have been only four studies that describe multi-twin, hierarchical or aggregated architectures; these are all conceptual or evaluated outside a continuous process. The 11 studies conducted in continuous or process manufacturing are at the level of one asset or one process model (Min et al., 2019; Choi, Choi and Lee, 2023; Jakubowski, Bobek and Nalepa, 2026). The most similar application to aggregation in continuous manufacturing is the pharmaceutical flowsheet twin, which models the unit operations in a continuous line, but has been used in product and process design, not for live risk prediction (Moreno-Benito et al., 2022).

5 CRITICAL ANALYSIS AND SYNTHESIS

5.1 Comparing findings across the reviewed literature

There are two sets of work here which do not have equal development and are positioned side by side. Digital twin-based condition monitoring and prediction maintenance for individual machines have been well studied (Chen et al., 2023), and these studies have all found that machine learning can be usefully integrated into a digital twin to aid fault detection and remaining useful life (RUL) estimation. Much less effort has been expended on making this possible to extend to combined, plant-wide representations. Lu et al. (2020) and Shao and Helu (2020) started to address how the individual twin should be designed to be connected together in larger systems to predict risk on a live production line; however, they did not report a working combination of twins used for risk prediction on a live production line.

A few newer studies start to fill this void. It is not a field that has been abandoned, as Redelinghuys, Kruger and Basson (2020) suggested one of the earliest architectures designed specifically for combining twins, and Khedr and Fitzgerald (2025) who looked at this more limited dataset directly, identified 21 qualifying papers published between 2022 and 2024, with a near doubling of papers per year in the most recent period covered. Most of this work, however, still relies on simulations instead of deployed systems to validate the proposed combinations, says their review. Häußermann et al. (2025) take it one step further and report a reality working system: individual twins for each device on a small production line, coordinated by a higher-level twin that reconfigures the line to order. It's a small scale demonstrator and not a continuous process as reviewed here, nor a continuous manufacturing system, but an actual implementation, not just a proposal. This is not a lack of development for digital twins integration, but a developing body of work that is young and mostly unproven in any real world application of the scale and process considered here.

The evidence for developing economies of industry is the same. Data-driven risk prediction for both critical assets in continuous or semi-continuous operations is shown in agent based self-diagnosis of induction furnace (Mashava et al., 2026) and machine-learning-based predictive maintenance for a power-station boiler (Senda et al., 2026), but neither of these connects the tracked asset to a representation of the entire process it supports.

5.2 Agreements and contradictions

The usefulness of a digital twin is as much as the data that links it to the physical counterpart: this is the distinction that Kritzinger et al. (2018) draw between a digital model, a digital shadow and a full digital twin, there is little doubt in this literature that this is the case. Likewise, there does not appear to be much contention that machine learning has been useful in prediction when there is sufficient data of failures in the past (Chen et al., 2023). The opinions on the maturity of the underlying technology are split in the literature. Digital twins are often presented in the language of an accomplished framework paper, and are already used for monitoring, optimisation and safety. Tao et al. (2019) are more conservative, and emphasize that there are still a number of systems available that do not consistently return the analytical results to the physical asset. They both are mentioned in the same literature, sometimes in the same year. Now, for a particular reason, this more conservative interpretation is taken as the working one in this review: a combined, plant-wide twin cannot do the risk prediction if the individual twins feeding it cannot. The contrast is instructive because closing the sense-decide-act loop is easy at the level of one device, as a smart wheelchair with a cheap ultrasonic obstacle-detection system that automatically stops the wheelchair within 50 cm distance of the obstacle shows (Munotyaani et al., 2026), but it is an architectural problem when multiple devices must agree on the state of a shared process.

5.3 Comparing methodologies

These sources do not all make the same sort of claims and it is not fair to equate their claims because some of the sources show less. Grieves and Vickers (2017) are at the level of definition and establish what a digital twin is not, rather than if it works. Lu et al. (2020) and Shao and Helu (2020) take it one step further: they propose reference architectures and requirements without actually implementing and testing anything. Van Dinter, Tekinerdogan and Catal (2022) and Chen et al. (2023) are closer to engineering practice, being concerned with how well particular machine-learning techniques perform on real maintenance data. This is a different Perno, Hvam and Haug (2022), one focusing on enablers and barriers, rather than a technical contribution. One of the newer ones is Häußermann et al. (2025) which is unusual in that they actually report a deployment, not a proposal or review of others' proposals. Designed-experiment studies fall in between – they create statically validated cause-effect relationships for a single process under controlled conditions, and, as stated by the authors, confirmation runs are necessary before optimal conditions can be transferred to production, thus providing trustworthy process models but not evidence of system level behaviour. None is a criticism of any single paper, because a definitional paper and an applied paper are really just doing different work; what this means is that a claim made in a paper based on Kritzinger et al. (2018) is different from a claim made in a paper based on Chen et al. (2023) in kind of evidential weight, and this synthesis does not pretend to level that difference.

5.4 Strengths and weaknesses of the current evidence base

There is a clear theoretical foundation, where there is no real challenge in any of the literature sources reviewed here, in the following points: what is a digital twin, what is the difference between digital twin and digital model/simulator/digital shadow, and the core usage of digital twin for predictive maintenance. Once the unit of analysis shifts from a single machine to a connected system, that settled base gets rather thin. While mostly still an architecture that is not built and run, this is not as slow as it may seem: Häußermann et al. (2025) report a small working aggregation, and the review by Khedr and Fitzgerald (2025) reveals real progress in the composition literature since 2022, even when formal validation methods do not keep up. This impression is translated into a quantified impression in the coding in Table 4. Few of the 50 studies included are empirical, fewer even refer to industrial data, and none of them reported on the use of an aggregated twin of real size and real-time implementation for the purpose of predicting the risk in industrial continuous manufacturing. The low mean score at the validation criterion (QA3 = 0.61) confirms the above. The problem of the lack of evidence is not the lack of concepts, but the lack of tested system level implementations of concepts.

5.5 Technological trends

There are four turns in this literature. Perhaps the biggest shift is from a digital twin that describes what is happening to one that predicts, and sometimes prescribes, what to do, with the latter going hand in hand primarily with the integration of big data analytics and machine learning, when the former was sufficient. In parallel, the relevance of standardisation is being given more prominence than ever, emblematic of which is the ISO 23247 framework highlighted by Shao and Helu (2020) as the mechanism promised to be the one that would enable the components of the Digital Twin to be composable on a broader system. The third shift is a change in data - the data sources are not only from individual sensors or individual machines, but are linked together across a process and are becoming more like a prerequisite than a byproduct. The fourth is enlargement of the concept of risk from equipment failure to operator

safety and ergonomics (Bevilacqua et al., 2020; Muhla et al., 2025b; Tandi et al., 2025), and extension of the notion of risk from operator safety and ergonomics to energy use as an explicit optimisation goal, along with quality (Tayisepi et al., 2023, 2024), consistent with the human-centric and sustainability emphasis of Industry 5.0.

6 RESEARCH GAPS AND FUTURE DIRECTIONS

A consistency runs through the taxonomy in Section 4 and the synthesis above: research on digital twins in manufacturing is well advanced at the individual asset level, but is much sparser at the aggregated system-wide level to which this review is focused. Gaps that follow directly are below. The most notable among these is that none of the validated industrial-scale digital twin aggregation is available. Lu et al. (2020) and Shao and Helu (2020) suggest reference models and requirements for twin combination, and Redelinghuys, Kruger and Basson (2020) proposed one of the earliest special architectures for twins. All of these is not built and operated on a large scale and the working demonstration by Häußermann et al. (2025) is not a large-scale, continuous industrial process but rather a small, single-line system.

The aggregation is not a demonstrated capability, but a proposed one. Future work requires pilot or industrial scale case studies where the connection between the twins is not only described, but also clarified in detail how data were shared between the twins, and how the joint output was validated with real data production. This can be supported by learning factories and hardware-in-the-loop testbeds that lie between simulation and plant deployment (Ndiyamba et al., 2026; Mashava et al., 2026). A related but different issue is what is being predicted. Existing research, such as van Dinter, Tekinerdogan and Catal (2022) and Chen et al. (2023), focuses on predictive maintenance for a single asset, predicting either RUL or identifying a new fault. This is a different problem than determining the effect that a failure will have on the flow, pressure, quality and output downstream of the failure in a continuous line.

A dimension of continuity risk across an interconnected process, as opposed to the health of a single machine, is not defined and validated anywhere in this literature, although Jones et al. (2020) identify this as an open issue. It is important to consider this as a research question and not as a continuation of asset level work. A third, mainly unresolved area is inter-operability. Recurring implementation challenges in the process industry are identified by Perno, Hvam and Haug (2022) as data integration, computational demand and lack of common standards, and Shao and Helu (2020) suggest ISO 23247, which was still in development at the time of writing, as the planned path for twin components to be reused and composed. Not a single instance of joining together two genuinely different platforms for the construction of twins is reported in the more recent composition literature as cited by Khedr and Fitzgerald (2025). However, it remains an open perspective question, whether this combination can be supported by an ISO 23247 aligned model, or an Asset Administration Shell implementation (Platenius-Mohr et al., 2020), or whether standardisation is a solved precondition. In addition to the aforementioned point, Tao et al. 2019 make another: Many digital twin systems available today fail to consistently feed back the analytical results back to the physical asset being represented.

The more the number of twins that are combined, the more important it is, because a system that cannot close the loop for its individual systems does not have a realistic chance of closing the loop at the system level. Closed-loop feedback should be considered a necessary precondition of the aggregation work and be explicitly reported in the future. A related, but distinct challenge is heterogeneous data integration, which is not aggregation specific, but rather a general challenge. Typically, sensor and IoT data, PLC/SCADA data, MES data, ERP data, and maintenance and quality records are all used together, but only for a single twin, not for multiple twins, each using one or more sources of data, that need to be reconciled with each other, as is confirmed by He and Bai (2021).

These are implementation issues, not conceptual issues, and future work should document practical approaches to this problem, rather than stating that it has data sources as an input and that the problem of reconciliation itself is not addressed. For situations where historical failure data is lacking, statistically designed experiments can provide a cost-effective method of seeding process models for the twin (Jansen et al., 2025; Mapindu et al., 2026), but it is not yet known how such locally fitted models can be integrated with data-driven asset models within an aggregate. One more deficiency is related to context. While the majority of the included studies are from well-resourced industrial environments, manufacturers in developing economies do have legacy equipment, disjointed connectivity, unreliable electrical power and limited digital skills (Muhla et al., 2025a; Ndiyamba et al., 2026). Results from these environments demonstrate that a plant-level aggregate could be formed using asset-by-asset deployments of the building blocks of aggregation, including the use of PLC-integrated sensor networks, agent platforms and machine-learning plant maintenance models, at reasonable cost on critical assets (Mashava et al., 2026; Senda et al., 2026), but no study has explored how such incremental asset deployments could be federated into a plant-level aggregate.

The field would greatly expand if there was research into lightweight and low-cost architectures for aggregation, and on the organisational agility required to react to signals of risks on the system-level (Muhla et al., 2023). Lastly, the risk functions studied in the literature are very limited in scope. In a separate series of works, human and ergonomic risk

(Muhla et al., 2025b; Tandi et al., 2025) and energy-related risk (Muyambo et al., 2025; Tayisepi et al., 2024) are dealt with. However, an operator error or a supply interruption can be propagated through a process in a continuous plant in the same way as an equipment fault. The logical evolution of aggregated twins to represent the condition of assets and the state of operators, in addition to energy flows, is the next step towards Industry 5.0's envisioned human-centric production systems that are sustainable.

There are also limitations in the evidence base of this review that impact on the confidence with which these gaps can be stated. The classification of Table 4 was coded at the level of detail that was reported in each paper, and some studies reported a short description of their architecture or validation only in a general way, so the proportions reported in Section 4.7 must be interpreted as indicative rather than exact. The search was also limited to four databases, only English language publications and twelve potentially relevant reports could not be obtained in full (Figure 1), meaning that some industrial implementations, especially those found in practitioner or regional publications, may not have been identified. There is one other restriction on the type of manufacturing this literature was created for.

The theoretical frameworks on which this review builds are mostly oriented towards discrete manufacturing (Grieves and Vickers, 2017; Kritzinger et al., 2018; Lu et al., 2020; Shao and Helu, 2020), as is the recent demonstrator of Häußermann et al. (2025). It remains to be seen whether aggregation frameworks designed for discrete manufacturing will apply in continuous manufacturing where one point of failure that impacts the entire process can have different and often more immediate effects. These gaps correspond to each of the research questions of the review. The gaps outlined are answers to RQ5; future reviews can track these gaps quantitatively via the coding scheme in Table 4, and they also include low-cost architectures appropriate to resource-constrained plants.

7 CONCLUSION

This systematic review explored the role Digital Twin Aggregates and big data analytics can play in predictive risk management in continuous manufacturing. The results indicate that Digital Twin technology is currently used in manufacturing on a wide scale for condition monitoring, fault detection and prediction. Most current research focuses on a single Digital Twin of a machine or a component, however, combining multiple Digital Twins to gain insights into how risk is being created and propagated throughout an interdependent production system has not been investigated. Only four out of 50 of the studies included are multi-twin or aggregated architectures and not one of those four studies is validated with industrial data in a continuous process.

This is still a critical constraint, particularly when considering continuous manufacturing as one part of the process can impact a downstream process, production continuity and product quality. The review identified that Digital Twins can be integrated by means of multi-twin, hierarchical and system-of-systems architectures, but the industrial scale implementation of these is still limited. Based on the research questions, the review concluded that Digital Twins can be integrated by using multi-twin, hierarchical and system-of-systems architectures but their industrial scale implementation is still limited. Information from sensors, IoT devices, PLC/SCADA systems, MES, ERP, maintenance records and historical production information can be analysed with the support of big data techniques like anomaly detection, predictive modelling and statistical analysis. These methods can be used to detect equipment failures, process deviations, quality issues, downtime and other risks that could impact production.

However, there are still a number of barriers to overcome in order to bring Digital Twin Aggregates to the industry. These include interoperability between different systems, integration of heterogeneous data, computational requirements, limited standardisation and the difficulty of maintaining closed-loop communication between physical equipment and its Digital Twin. The review also identified that a significant amount of the current work has been limited to developing work for individual assets and discrete manufacturing; and there were limited examples of work that comes from a real continuous manufacturing setting, or from developing industrial economies. In conclusion, Digital Twin Aggregates in conjunction with big data analytics offer a promising strategy for shifting predictive risk management from one machine to a system perspective of manufacturing risk. But more investigations are needed to validate these systems employing actual continuous manufacturing processes in industry.

Future research should especially be directed toward practical implementation of multiple Digital Twins, methods for sharing data in an interoperable and mutually agreed way, system level risk prediction, not only based on the machine level, but also on the human and energy level, low-cost architectures that can be implemented in resource-constrained plants, and approaches for assessing how failures in one component of a continuous process affect the remaining parts of the production system.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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The authors declare no conflict of interest.

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