The Role of Digital Twins in Optimizing and Transforming Operations Management

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Abstract
A digital twin is a virtual representation of a physical object or system. It is like a digital mirror that reflects the state and behaviour of its real counterpart. This virtual representation can be used to simulate, analyse and optimise the physical object or system. This paper explores the transformative potential of digital twins to revolutionise operations management. By creating virtual replicas of physical assets and processes, digital twins offer unprecedented opportunities to optimise performance, improve *decision* making and increase operational efficiency. This study looks at the applications of digital twins in various industries and examines their impact on supply chain management, production planning, asset management and predictive maintenance. In addition, the study explores the challenges and opportunities associated with implementing digital twin technology, including data management, cybersecurity and organisational readiness. The findings of this study contribute to a deeper understanding of how digital twins can be utilised to drive operational excellence and create sustainable competitive advantage. Ultimately, this study aims to provide insights into the role of digital twins in shaping the future of operations management.

Keywords: Digital twins, operations management, Industry 4.0, simulation, optimization, predictive maintenance

Introduction

A digital twin is a virtual image of a physical unit, a process or a system. It is created using data from sensors, simulations and other sources (Liu, Zheng, & Bao, 2024; Koo & Yoon, 2024; Tuhaise, Tah, & Abanda, 2023). This digital representation can be used to monitor, analyse and predict the behaviour of the physical unit. In manufacturing, a digital twin of a factory can be used to optimise production processes, identify bottlenecks and improve efficiency (Kumbhar, Ng, & Bandaru, 2023; Javaid, Haleem, & Suman, 2023). In infrastructure, a digital twin of a bridge or building can be used to monitor the condition of the structure, predict maintenance needs and simulate the impact of natural disasters (Braik & Koliou, 2023; Jeon, Shim, Lee, & Schooling, 2024). In healthcare, a digital twin of a patient can be used to personalise treatment plans, simulate surgical procedures and monitor health outcomes. In cities, a digital twin of a city can be used to optimise traffic flow, manage waste and plan future development.

Key features of a digital twin include virtual representation (a digital model that mirrors a real object or system), real-time data (receives data from sensors or other sources to always be up to date), predictive analytics (can be used to predict future behaviour or outcomes) and simulations (can be used to simulate different scenarios and test hypotheses). Digital twins have become a transformative technology in the field of operations management, offering unprecedented opportunities to optimise processes, increase efficiency and drive strategic decision-making. At its core, a digital twin is a virtual representation of a physical asset, system

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or process that is continuously updated with real-time data to mirror its real-world counterpart. The integration of digital twins into operations management has led to tangible benefits in various industries. By creating a detailed digital representation of physical assets, operations managers can simulate and test scenarios, predict maintenance requirements and pre-emptively address potential problems before they occur in the real world.

The ability to perform "what-if" analyses in the digital space has proven invaluable, enabling companies to optimise production processes, improve resource utilisation and increase sustainability. The use of digital twins goes beyond manufacturing and is being applied in various fields such as personalised medicine, oil refinery management, risk detection and urban planning (Thelen, et al., 2022; Knebel, Trevisan, do Nascimento, Abel, & Wickboldt, 2023). The impact of digital twins on operations management is profound as they enable a paradigm shift from reactive to proactive decision-making (Attaran, Attaran, & Celik, 2024; Longo, Padovano, De Felice, Petrillo, & Elbasheer, 2023). The concept of the digital twin has gained acceptance in the manufacturing industry and offers a powerful tool for optimisation, simulation and predictive maintenance (Hornik & Rachamim, 2024). Digital twins create a virtual representation of a physical plant, process or system and provide a dynamic and data-driven model that can be used to simulate scenarios, predict performance and optimise operations (Perno, Hvam, & Haug, 2022; Guo, et al., 2024).

Main and Specific Objectives

This study explores the transformative potential of digital twins in optimising and revolutionising operations management. By creating virtual replicas of physical assets and processes, digital twins offer unprecedented opportunities to improve decision-making, increase efficiency and drive innovation. This study explores the application of digital twins in various operational areas, including supply chain management, production and asset management. It also looks at the challenges and opportunities associated with implementing and scaling digital twin technology. The findings of this study contribute to a deeper understanding of how digital twins can be utilised to drive operational excellence and create sustainable competitive advantage.

The paper critically analyses and summarise the existing literature on the application of digital twin technology in operations management to assess how it optimises and transforms various aspects of operational processes, decision making and performance.

Specific objectives

i. Exploring the concept of digital twins and their applications in different fields of use;
ii. Evaluate the impact of digital twins on operational efficiency;
iii. Investigate the role of digital twins in decision-making processes;
iv. Exploring the transformation of operational management practises; and
v. Develop a conceptual model for implementation of digital twins in developing countries.

Significance

A better understanding of digital twins: This paper provides a comprehensive overview and synthesis of the current literature on digital twins to further the understanding of this emerging technology. By clarifying the conceptual framework and operational functionalities of digital twins, the paper contributes to a deeper understanding of how these virtual replicas are revolutionising operations management.

Decision-making practises: By exploring how digital twins support decision making through real-time data analytics, predictive modelling and scenario simulations, the paper sheds light on their impact on strategic and tactical decisions. This information is valuable for managers and decision makers who want to improve their decision-making processes with advanced technological tools. Facilitating change in operations management: The paper explores the transformative impact of digital twins on traditional operations management practises. It demonstrates how these technologies are driving innovation in areas such as maintenance strategies, supply chain management and production planning. Understanding these changes will help organisations adapt to evolving industry standards and practises.

Dealing with challenges and constraints: By addressing the challenges and limitations associated with implementing the digital twin, such as issues with data integration and model accuracy, the paper provides a balanced view of the practical implications of the technology. This critical perspective is essential for stakeholders to overcome potential obstacles and make informed decisions about the adoption of digital twin solutions. Guide future research and development/contribute to academic and practical knowledge: The paper identifies gaps in the existing literature and suggests future research directions. By suggesting areas for further exploration, it encourages continued innovation and development in the field of digital twins and ensures that advances continue to meet emerging needs and opportunities in operations management. This review is a valuable resource for both academics and practitioners. For researchers, it provides a consolidated overview of the current state of knowledge and identifies areas for further investigation. For practitioners, it provides actionable insights on how digital twins can be used effectively to improve operational performance and achieve strategic goals.

Scope

The paper deals with digital twin technology and includes its definitions, theoretical foundations and core components. It explains how digital twins function as virtual replicas of physical assets, processes or systems and the role they play in operations management. The scope includes an examination of the applications of digital twins in various areas of operations management, such as process optimisation, resource management, maintenance strategies and supply chain management. It examines how these applications contribute to operational efficiency and effectiveness. It summarises findings from various sources to provide a comprehensive overview of their impact on operations management over the last three years.

Literature Review

Digital twin technology, a concept that originated in the field of simulation and modelling, has become increasingly important in the field of operations management over the last decade. This literature review explores the development, applications, benefits and challenges of digital twins, drawing on a range of academic sources and industry reports to provide a comprehensive understanding of their impact on operations management. The concept of the digital twin was first introduced by Michael Grieves in 2002, initially to describe a virtual representation of physical assets (Grieves, 2002). Since then, the concept has evolved to encompass more complex systems, including processes and entire organisations. A digital twin integrates real-time data from physical counterparts to create a dynamic virtual model that reflects the current state of its real-world counterpart (Tao, Zhang, Liu, & Nee, 2018). This model enables the simulation, analysis and optimisation of physical plants or processes.

Applications in Operations Management

Digital twins have found a variety of applications in different areas of operations management. In manufacturing, digital twins are used to optimise production processes through real-time monitoring and simulation. The use of digital twins in predictive maintenance, for example, enables companies to anticipate equipment failures before they occur, thus minimising downtime and maintenance costs (Javaid, Haleem, & Suman, 2023; Patel, Shah, Lella, & Gajbahar, 2024). In supply chain management, digital twins enable end-to-end transparency and help to synchronise production plans with fluctuations in supply and demand (Zaidi, Khan, & Chaabane, 2024; Freese & Ludwig, 2024). A prominent application is building management, where digital twins provide insights into energy consumption, space utilisation and environmental conditions. By modelling the operational aspects of a building, building managers can optimise energy consumption, improve occupant comfort and reduce operating costs (Ghansah, 2024; Tuhaise, Tah, & Abanda, 2023). Digital twins also help in logistics to optimise route planning and inventory management by simulating different scenarios and outcomes (Belfadel, et al., 2023; Vinci-Carlavan, Rossit, & Toncovich, 2024).

Impact on Operational Efficiency and Decision-Making

Digital twins improve operational efficiency by facilitating real-time data analysis and simulation. They provide actionable insights that support continuous improvement efforts. For example, by simulating different operational scenarios, digital twins help managers identify inefficiencies and test potential solutions in a virtual environment before implementing them in the real world (Walton, Ciarallo, & Champagne, 2024; Abo-Khalil, 2023). This capability is critical to making informed decisions that align with strategic goals. In addition, digital twins support advanced decision-making through the integration of big data and AI. AI algorithms can analyse the vast amounts of data generated by digital twins to identify patterns and predict future performance, enabling proactive decision-making (Kaul, et al., 2023; Currie, 2023). This integration of AI with digital twin technology improves the accuracy of predictions and optimises decision-making processes in complex operating environments.

Challenges and Limitations

Despite their benefits, digital twins face some challenges and limitations. Data integration is a major hurdle, as digital twins rely on accurate and timely data from multiple sources. Inconsistent or incomplete data can affect the reliability of the digital twin model (Aghaabbasi & Sabri, 2025). In addition, the complexity of creating and maintaining digital twins can be resource-intensive and require significant investment in technology and skilled personnel. The accuracy of the model and its validation are also critical. Ensuring that the digital twin accurately represents its physical counterpart requires ongoing calibration and validation, which can be challenging in dynamic environments (Eneyew, Capretz, & Bitsuamlak, 2024). In addition, the scalability of digital twin solutions can be limited, especially for smaller organisations or those with a less advanced technological infrastructure.

Methodology

When identifying relevant databases, the existing literature was first reviewed to identify databases that are frequently used in research on operations management and digital twin. The focus was on databases containing comprehensive academic articles, interdisciplinary research, a wide range of academic articles, management-focused studies, interdisciplinary research and peer-reviewed articles, and citation data. The inclusion criteria were relevance (articles must focus on digital twins in the context of operations management), timeliness (recent publications, e.g. 2-3 years ago, to ensure current trends and technologies are considered), quality (selection of peer-reviewed journals); diversity (inclusion of studies from different industries to provide a holistic view); peer-reviewed journals (articles published in reputable academic journals) and language (English language articles). Primary and secondary keywords were used in the systematic search. Primary keywords were digital twin, operations management, optimisation, transformation, manufacturing, supply chain, maintenance, simulation, while secondary keywords were Industry 4.0, Internet of Things (IoT), AI, machine learning, predictive maintenance, virtual reality, augmented reality.

The identified articles were screened. Initial screening of titles and abstracts to exclude irrelevant studies. For articles that met the preliminary criteria, a full-text review was performed to assess relevance and quality. Finally, the data was extracted using a form in which key information such as authors, year of publication, research focus, methods used and main results were recorded. The data was then analysed and summarised on the topics of optimisation techniques, impact on decision making, integration with existing systems and challenges and limitations. A comparative analysis of the results of different studies was then carried out to identify trends, gaps and future research directions. By applying this methodology, the literature review will provide a solid foundation for understanding the role of digital twins in optimising and transforming operations management and contribute to both academic and practical knowledge in this area.

Results

Digital Twins in Decision-Making Processes

Digital twins enable organisations to make more informed, data-driven decisions based on real-time insights, simulations and predictive analytics. Whether it's operational improvements, risk management, cost reductions or long-term strategic planning, digital twins can optimise processes, improve results and drive innovation. As digital twin technology continues to evolve, its role in decision-making is likely to become even more central as the capabilities of AI, machine learning and integration with broader digital ecosystems increase.

Strategic Planning and Long-Term Vision

Digital twins support strategic, long-term decision-making. For example, a city’s digital twin can help policy makers assess the long-term needs of infrastructure such as transport or energy systems and test different growth scenarios (Li, Yang, & Wu, 2024; Padovano, Longo, Manca, & Grugni, 2024). Similarly, a digital twin of a power plant can support decisions on the modernisation, decommissioning or capacity expansion of plants (Yassin, Shrestha, & Rabie, 2023).

Real-Time Data Integration for Informed Decisions

Digital twins integrate real-time data from sensors, IoT devices and other sources to create a constantly updated virtual model. This provides decision-makers with accurate, up-to-date information, which can be critical in situations that require quick, data-driven decisions (Su, et al., 2024; Kanaga-Priya & Reethika, 2024). In manufacturing, for example, a digital twin of a factory could monitor machine performance in real time, allowing operators to adjust processes or take corrective action before breakdowns occur, increasing productivity and reducing downtime. One of the most powerful features of digital twins is their ability to simulate different scenarios. By adjusting variables in the digital model, companies can predict the impact of different decisions before making them in the real world. In the energy sector, for example, a digital twin of an electricity grid can simulate the impact of increased demand, the introduction of renewable energy sources or an equipment failure, helping managers make decisions to optimise grid stability, efficiency and costs (Ismail, Al-Faiz, Hasini, Al-Bazi, & Kazem, 2024). Predictive analyses supported by digital twins also help predict future outcomes based on current and historical data (Hellenborn, Eliasson, Yitmen, & Sadri, 2024). This gives decision-makers valuable insights into long-term trends or the possible consequences of different decisions.

Optimisation of Processes and Resources

Digital twins help to optimise processes by identifying inefficiencies and suggesting improvements. In supply chain management, for example, a digital twin of the entire supply chain enables managers to visualise and evaluate bottlenecks, production rates and logistics in real time (Espinosa-Jaramillo, et al., 2024; Bakhshi, et al., 2024). This enables more efficient resource allocation, better inventory management and the ability to switch quickly in the event of disruptions (e.g. a natural disaster or supply chain disruption). In product design and development, digital twins help teams test prototypes virtually, reducing the need for physical prototypes and speeding up the development cycle. Companies can simulate how a product will behave under different conditions, identify design flaws early and make iterative improvements to ultimately bring better products to market faster and more cost-effectively.

Risk Management and Risk Minimisation

Digital twins also play a crucial role in risk management, as they enable companies to anticipate and mitigate risks before they materialise. In the construction industry, for example, a digital twin of a construction project can simulate how various environmental factors (such as weather or seismic activity) could affect the structure so that engineers can take preventative measures (Tuhaise, Tah, & Abanda, 2023; Long, Bao, Chen, Ng, & Wuni, 2024). By enabling more efficient decision-making, reducing the need for physical tests and improving resource allocation, digital twins can lead to significant cost savings (Barth, Schweiger, Benedech, & Ehrat, 2023). In industries such as aerospace or automotive manufacturing, where prototyping and testing are expensive, digital twins can reduce costs by allowing companies to validate designs and digitally optimise operations before allocating resources to physical production or infrastructure changes (Panarotto, Isaksson, & Vial, 2023).

Improved Collaboration and Communication

Because digital twins provide a shared, up-to-date view of a system or facility, they improve collaboration between different stakeholders. For example, on a large infrastructure project, architects, engineers and contractors can all access the project's digital twin to coordinate their work, assess design changes and ensure everyone is up to date (Moshood, Rotimi, Shahzad, & Bamgbade, 2024; Kor, Yitmen, & Alizadehsalehi, 2023). This real-time collaboration can reduce delays, misunderstandings and errors, leading to better decision-making and faster execution. Digital twins are not static, but evolve over time as more data is collected. This continuous flow of data allows for continuous improvement in decision making. For example, a manufacturer using a digital twin to monitor a production line can continuously refine the process based on feedback from the virtual model, incrementally improving efficiency, safety and performance (Fu, Liu, & Li, 2024; John & K, 2024).

Transformation of Operational Management Practises

The emergence of digital twin technology has revolutionised the field of operations management, offering unprecedented opportunities to optimise and transform various industrial processes. Digital twins, defined as virtual representations of physical systems, have the potential to integrate multidisciplinary, multiphysical and multiscale numerical methods that enable comprehensive modelling of real processes and plants (Thelen, et al., 2022; Zhang, et al., 2020). This integration of physical models, sensor data and operational data can lead to improved decision-making, predictive maintenance and full cycle management. The concept of the digital twin originated in the field of advanced manufacturing, where it is widely used in areas such as automated production, predictive maintenance and full life cycle management (Zhang, et al., 2020). In the age of big data, the wealth of data generated throughout the product lifecycle can be used to create digital models for simulations and analyses. This closes the digitalisation loop and provides decision-makers with actionable insights (Thelen, et al., 2022). One of the key benefits of digital twins is the ability to optimise control and maintenance actions for individual units, as well as the potential to optimise the design of next-generation products. This emerging technology poses new and challenging optimisation problems at the forefront of model-based design, smart manufacturing, industrial internet of things, machine learning and predictive maintenance.

Importance of Digital Twin in Business Operations

The future of digital twins is bright, with advances in artificial intelligence, machine learning and IoT technologies driving innovation. As digital twins become more sophisticated, they will play an even more important role in transforming operational management practises across all industries (Attaran, Attaran, & Celik, 2024; Broo & Schooling, 2023). Predictive maintenance is a strategic approach to maintenance that uses data analytics and sensor technology to predict potential equipment failures before they occur. This proactive approach offers numerous advantages over traditional reactive or preventative maintenance strategies. Predictive maintenance can utilise digital twins for real-time monitoring (Hu, Wang, Tan, & Cai, 2023). By continuously monitoring the digital twin, potential equipment failures can be predicted before they occur (Javaid, Haleem, & Suman, 2023; Wang, et al., 2024). In addition, digital twins can help optimise maintenance schedules to reduce downtime and increase operational efficiency.

Process optimisation is the art and science of refining business processes to maximise efficiency, reduce costs and improve overall performance. It is a strategic approach that can have a significant impact on an organisation's bottom line and customer satisfaction. The digital twin can be used to simulate and optimise by simulating different operational scenarios to identify bottlenecks and inefficiencies (Kumbhar, Ng, & Bandaru, 2023; Javaid, Haleem, & Suman, 2023). Companies can then continuously improve their processes by analysing real-time data and simulation results. When optimising the supply chain, digital twins can provide real-time insights into the entire supply chain, from the procurement of raw materials to the delivery of the final product. By analysing historical data and real-time trends, companies can accurately forecast demand and optimise inventory levels (Espinosa-Jaramillo, et al., 2024). Quality control is the process of ensuring that products or services meet certain quality standards. It is a critical component of business operations. Real-time quality monitoring through digital twins can monitor product quality in real time and detect defects at an early stage. By simulating different manufacturing processes, quality assurance teams can proactively address potential issues (Soori, Arezoo, & Dastres, 2023; Maheshwari & Devi, 2024).

Remote command and control refers to the ability to manage, monitor and control activities remotely, usually through digital technologies. This means that operators can monitor and influence processes or systems without being physically on site (Hu, Qiu, Jing, Tang, & Zhu, 2023; Padovano, Longo, Manca, & Grugni, 2024). Digital twins enable remote monitoring and control of equipment, reducing the need for on-site personnel. Remote troubleshooting: Problems can be detected and rectified remotely, minimising downtime.

Model Components

The development of models is the cornerstone for a successful implementation of the digital twin and plays a crucial role in the optimisation and transformation of operations management. By creating accurate virtual representations of real systems, organisations can unlock a wealth of insights and opportunities. A conceptual implementation model serves as a basic framework for understanding how a particular process, intervention or system can be brought from theory to practise. It serves as a guide for those involved in the implementation of projects, providing both clarity and direction. Whether in business, healthcare, education or technology, developing an effective conceptual implementation model is essential to achieving sustainable outcomes and managing the complexity that arises when turning ideas into real-world applications. This essay explores how a conceptual realisation model can be developed. It covers the key components, the stages of its creation and strategies for refining and applying the model. Figure 1 is a proposed implementation of digital twins.

1. Identify target systems and goals	Select critical systems: Identify the systems or processes that would benefit most from digital twin technology, such as manufacturing lines, supply chains or energy systems.
	Define goals: Clearly articulate the specific goals of the digital twin, e.g. improved efficiency, reduced downtime, improved product quality or optimised resource utilisation.
2. Data collection and integration	Data sources: Identify and integrate data from multiple sources, including sensors, IoT devices, ERP systems and historical data.
	Ensure data quality: Ensure data quality, consistency and completeness to create accurate and reliable digital twins
	Data integration platform: Build a robust data integration platform to consolidate data from different sources
3. Development of the digital twin	Model selection: Select appropriate modelling techniques based on the complexity of the system and availability of data, e.g. physics-based, data-driven or hybrid models
	Development of the model: Develop detailed digital twin models that accurately represent the behaviour and interactions of the physical system.
	Validation and verification: Validate the digital twin models against real-world data to ensure accuracy and reliability.
4. Simulation and analysis	Scenario analysis: Perform "what-if" simulations to evaluate the impact of different decisions and scenarios on the performance of the system.
	Optimisation: Use optimisation techniques to determine optimal operating conditions and decision strategies.
	Predictive analyses: Use predictive analyses to forecast future trends and potential disruptions.
5. Real-time monitoring and control	Real-time data integration: Continuously update the digital twin with real-time data from sensors and IoT devices
	Real-time monitoring: Monitor key performance indicators (KPIs) and detect anomalies or deviations from expected behaviour
	Real-time control: Implement closed-loop control to automatically adjust system parameters and optimise performance
6. Collaboration between man and machine	User-friendly interfaces: Develop intuitive user interfaces to facilitate interaction with the digital twin.
	Augmented reality and virtual reality: Use AR/VR technologies for better visualisation and decision-making
	Training and education: Provide training to operators and engineers so they can use the digital twin effectively.
7. Continuous	Feedback loops: Create feedback loops to continuously improve the accuracy and effectiveness of the digital twin.

improvement and learning	Machine learning: Use machine learning algorithms to automatically recognise patterns and trends in data.
	Adaptive models: Develop adaptive models that can learn and evolve over time.

Figure 1: Implementation of Digital twins
Source: Literature review

Conclusion and Recommendations

This research investigated the transformative potential of digital twins in optimizing and revolutionizing operations management. By creating virtual replicas of physical assets and processes, digital twins offer unprecedented opportunities to enhance decision-making, improve efficiency, and foster innovation. This study explores the application of digital twins across various operational domains, including supply chain management, production, and asset management. Furthermore, it delves into the challenges and opportunities associated with implementing and scaling digital twin technology. The findings of this research contribute to a deeper understanding of how digital twins can be leveraged to drive operational excellence and create sustainable competitive advantages.

Conclusion

To summarise, the integration of digital twins into operations management represents a paradigm shift in the way companies approach efficiency, innovation and decision-making. By creating virtual replicas of physical plants and processes, digital twins offer unrivalled insight into real-world operations. This paper has explored the multi-faceted role of digital twins in optimising and transforming operations management. Key areas where digital twins have proven their worth include predictive maintenance, real-time monitoring, scenario planning and product design. By leveraging data-driven insights and advanced analytics, digital twins enable companies to anticipate potential problems, make proactive decisions and optimise resource allocation. As the technology evolves, the applications of digital twins are expanding and promise to revolutionise the entire industry. To take full advantage of digital twins, organisations need to invest in a robust data infrastructure, advanced analytics capabilities and skilled personnel. By utilising this transformative technology, companies can unlock new levels of operational excellence and gain a competitive advantage in the digital age.

Recommendations

The paper provides a comprehensive exploration of how digital twin technology can be used to increase operational efficiency, improve decision-making and drive transformation in organisations. Digital twins, as virtual replicas of physical systems, processes or products, enable real-time data integration and predictive analytics and offer immense potential for improving operations management in various industries. Although this paper covers the most important aspects of digital twins, some areas could be expanded upon to provide a deeper, more holistic understanding of the role of this technology in operations management. Several recommendations are made in this paper to strengthen the content of the paper and improve its applicability for both academics and industry professionals.

Inclusion of Industry-Specific Case Studies

One of the key recommendations is the inclusion of more detailed, real-world case studies that demonstrate how digital twin technology has been successfully utilised in different industries. Although the paper provides a general overview of digital twins, the lack of specific examples may leave readers with a limited understanding of how this technology is being utilised in practise. Case studies from different sectors — such as manufacturing, healthcare, logistics, energy and aerospace — could provide valuable insights into the unique challenges, benefits and outcomes associated with implementing digital twins in an operational environment. For example, a manufacturing company could use a digital twin to optimise production lines by simulating different scenarios and adjusting processes in real time. Similarly, in healthcare, digital twins of hospital equipment or patient conditions could improve predictive maintenance and optimise resource allocation. Through a sector-specific study of digital twins, the paper could demonstrate the versatility and adaptability of this technology in different operational contexts.

Investigate Integration with other Emerging Technologies

Another key recommendation is to explore the synergies between digital twins and other emerging technologies such as AI, the IoT and blockchain. While digital twins are themselves a powerful tool for improving operations, they often rely on and interact with other advanced technologies to realise their full potential. In combination with AI, for example, digital twins can enable predictive maintenance and anomaly detection by continuously learning from operational data. In IoT-enabled environments, digital twins can be fed with real-time data from sensors embedded in physical assets, enabling more accurate modelling and decision making. In addition, the integration of blockchain could help ensure the security and integrity of the data used by digital twins, which is particularly important in industries such as supply chain management or healthcare. Exploring these overlaps would not only strengthen the role of digital twins in operations management, but also provide a more nuanced understanding of how different technologies work together to drive operational excellence and innovation.

Provide a Cost-Benefit Analysis and ROI Metrics

A third recommendation concerns the inclusion of a detailed cost-benefit analysis and metrics to measure return on investment (ROI) when implementing digital twin technology in operations management. Many organisations are reluctant to adopt new technology due to concerns about cost, complexity and potential disruption. Financial metrics or examples of how organisations have measured the impact of digital twins on their operations would provide concrete evidence of the value these systems can deliver. The paper could explore questions such as: What are the costs associated with implementing a digital twin? What kind of ROI can companies expect in terms of operational efficiency, cost savings or improved product quality? By analysing more quantitatively, the paper could better address the concerns of decision makers evaluating the financial feasibility of implementing digital twin technology.

Consider the Human and Organisational Impact

The introduction of the digital twin is not only a technological change, but also an organisational and cultural one. One recommendation for the extension of the paper is to explore the human and organisational changes required for the successful adoption of the digital twin. This could include discussions on workforce adaptation, training and overcoming resistance to change. Digital twin systems may require employees to adopt new ways of working, from understanding complex data analyses to interacting with digital models in real time. The paper could discuss how organisations can support their employees through this transition by providing training programmes, re-skilling opportunities and strategies to promote a culture of data-driven decision making. In addition, the potential for job displacement through automation and strategies for dealing with these changes in a socially responsible way could be discussed.

Consideration of Ethical and Data Protection Concerns

As digital twins rely on the continuous collection of data — often from sensors embedded in physical objects — there are potential ethical and privacy concerns that should be considered. A key recommendation is to discuss these concerns and establish guidelines for ethical data use and best security practises. For example, organisations must ensure that they comply with data protection regulations when collecting and processing personal or sensitive data. In addition, the use of digital twins to track individuals, monitor employee performance or optimise customer behaviour raises ethical questions about the monitoring and ownership of data. By addressing these issues, the paper could provide a more comprehensive overview of the challenges associated with digital twin technology and make recommendations on how organisations can mitigate the risks while ensuring ethical practises.

Long-term Sustainability and Environmental Impact

Sustainability has become an important issue for organisations around the world, and digital twins have the potential to play an important role in helping companies achieve their environmental goals. A valuable addition to the paper would be an exploration of how digital twins can contribute to sustainability efforts, such as reducing waste, optimising energy consumption or improving resource allocation. For example, a digital twin could simulate the energy consumption of a production plant and identify opportunities for energy savings. In supply chain management, digital twins could help to optimise logistics routes and thus reduce fuel consumption and carbon emissions. By exploring the environmental benefits of digital twins, the paper could align with current trends in corporate responsibility and sustainability, which are becoming increasingly important to stakeholders, regulators and consumers.

Addressing Challenges in Data Quality and Modelling Accuracy

Finally, the paper could shed more light on the challenges associated with data quality, modelling accuracy and the ongoing maintenance of digital twins. The effectiveness of a digital twin is highly dependent on the quality of the data it receives and the accuracy of the models it simulates. A common challenge in many organisations is the inconsistent or incomplete data that may be available for modelling, as well as the complexity associated with creating and updating accurate digital models. The paper could explore practical strategies for ensuring high quality data collection as well as approaches for improving the accuracy of digital twin simulations. This could include the use of advanced machine learning algorithms to improve prediction accuracy or the integration of real-time data streams to continuously update the digital twin. Addressing these challenges would give readers a clearer picture of how to overcome common obstacles to implementing digital twins in their operations.

Areas for Further Studies

The paper lays a solid foundation for understanding the potential of digital twins to revolutionise operations management. However, further research is needed in numerous areas, particularly in relation to the standardisation of digital twin systems, integration with artificial intelligence and machine learning, human factors, ethical concerns, financial implications, sustainability and supply chain optimisation. By addressing these research gaps, future studies can provide a more comprehensive understanding of the challenges, opportunities and best practises for the adoption of digital twin technologies in operations management. These efforts will help organisations realise the full potential of digital twins and drive innovation in their operations.

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