العلاقة بين التوأمة الرقمية والأداء المستدام: دراسة للشركات الصناعية السعودية

Digital Twins and Sustainable Performance: A Study of Saudi Manufacturing Firms

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Abstract

The integration of Digital Twin (DT) technology is to reshape manufacturing practices by improving operational efficiency and promoting sustainability. This study investigated the relationship between Digital Twin Readiness (DTR), encompassing Technological and Data Readiness (TDR), Organizational Readiness and Support (ORS), and Perceived Values and Benefits (PVB), and the dimensions of Sustainable Performance (SP) within Saudi manufacturing firms. This study administered a structured survey to 201 managerial respondents from Saudi manufacturing firms. The collected data was subsequently analyzed using Partial Least Squares-Structural Equation Modeling (PLS-SEM). The study's results demonstrated that the dimensions of DTR positively and significantly contribute to SP. These findings emphasize the critical need for strategic efforts to promote DT adoption, particularly through investments in infrastructure, employee training, and the resolution of related challenges. This study contributes to the existing body of knowledge by addressing a critical gap in understanding the influence of DTR on sustainable manufacturing practices. It provides valuable practical implications for industry leaders and policymakers, offering guidance on the development of effective strategies for DT adoption aimed at improving sustainability outcomes and enhancing operational efficiency.

Keywords: Digital Twin – Industry 4.0 – Smart Manufacturing – Sustainable Performance –Readiness – Manufacturing Firms.

الملخص

يشهد القطاع الصناعي في المملكة العربية السعودية تحولًا ملحوظًا في ممارساته التشغيلية نتيجة دمج تقنية التوأمة الرقمية، حيث تسهم هذه التقنية في رفع كفاءة العمليات وتعزيز مفاهيم الاستدامة. وفي هذا السياق، هدفت هذه الدراسة إلى تحليل العلاقة بين مدى جاهزية الشركات الصناعية السعودية لتكنولوجيا التوأمة الرقمية، والتي تشمل: الجاهزية التكنولوجية وجاهزية البيانات، الدعم والجاهزية التنظيمية، والفوائد المتوقعة، وبين أبعاد الأداء المستدام (الاقتصادي، الاجتماعي، والبيئي) داخل الشركات الصناعية السعودية. وقد اعتمدت الدراسة على استبيان تم توزيعه على عينة مكونة من ٢٠١ من المديرين العاملين بالشركات الصناعية في المملكة العربية السعودية، وتم تحليل البيانات باستخدام نمذجة المعادلات الهيكلية PLS-SEM. أظهرت نتائج الدراسة أن أبعاد الجاهزية للتوأمة الرقمية تؤثر بشكل إيجابي ومعنوي على ابعاد الأداء المستدام، تبرز هذه النتائج أهمية تبني استراتيجية لتعزيز استخدام تقنية التوأمة الرقمية في الشركات الصناعية السعودية، لا سيما من خلال الاستثمار في البنية التحتية، وتدريب العاملين، ومعالجة التحديات المرتبطة بتطبيق هذه التكنولوجيا، تساهم هذه الدراسة سد الفجوة البحثية المتعلقة بتأثير جاهزية الشركات الصناعية لتطبيق تكنولوجيا التوأمة الرقمية على ممارسات التصنيع المستدامة، كما تقدم مجموعة من التوصيات العملية لمديري الشركات الصناعية وغيرهم من صناع السياسات بهدف تبني استراتيجية فعالة تهدف إلى تبني تكنولوجيا الثورة الصناعية الرابعة، مثل التوأمة الرقمية، بهدف تحسين نتائج الاستدامة ورفع كفاءة الأداء التشغيلي.

الكلمات المفتاحية: التوأمة الرقمية – الثورة الصناعية الرابعة – التصنيع الذكي – الأداء المستدام – الجاهزية – الشركات الصناعية.

Introduction:

Emerging as a prominent concept in the 1980s, "sustainability" has since played a pivotal role in shaping the strategies and operations of numerous businesses (Hami et al., 2015; Kidd, 1992; Rosário & Dias, 2022). For manufacturing firms, sustainable performance extends beyond traditional financial metrics and short-term economic gains, encompassing a broader framework that integrates economic, environmental, and social dimensions of sustainability, known as The Triple Bottom Line (TBL) (Alshehhi et al., 2018; Buhaya & Metwally, 2024). Despite recent technological advancements and the digitalization of manufacturing processes, manufacturing firms have increasingly emerged as significant contributors to environmental degradation and the depletion of natural resources (Buhaya & Metwally, 2024; Herva et al., 2011). This trend is largely attributed to the continued reliance on traditional business practices, which are characterized by high levels of energy and resource consumption, along with significant environmental consequences (Buhaya & Metwally, 2024; Joshi & Sharma, 2022).

In light of these challenges, the intersection of Industry 4.0 technologies and sustainability has become a focal area of interest for scholars, industry practitioners, and policymakers alike (Akbari & Hopkins, 2022; Bohnsack et al., 2022; Ejsmont et al., 2020; Lopes de Sousa Jabbour et al., 2018). Sharma et al. (2025) assert that Industry 4.0 technologies hold significant potential to enhance operational efficiency, lower costs, and advance both productivity and sustainability within industrial settings. Acknowledging the critical role of sustainability in the manufacturing sector (Ahmad & Zabri, 2016; Bosman et al., 2020; Liu et al., 2024; Nayal et al., 2024; Rashid et al., 2024), Saudi Arabia has actively encouraged the broader adoption of smart manufacturing practices as part of its Vision 2030 agenda. This national strategy aims to enhance industrial performance and integrate sustainable practices into business operations (Alharbi, 2024; Patil et al., 2024). Consequently, there has been a notable increase in investments directed toward automation and smart manufacturing technologies, often referred to as digitalized or intelligent manufacturing (Alharbi, 2024).

Smart manufacturing consists of integrated and collaborative systems that adapt in real time to dynamic factory and supply network conditions, ensuring efficiency and responsiveness to evolving customer demands (Kusiak, 2018; Zheng et al., 2018). The transition to smart manufacturing has been facilitated by the advancement of data acquisition systems, IT, and network technologies (Tao & Qi, 2017; Tao et al., 2019). A fundamental enabler of smart manufacturing is Digital Twin (DT) technology. DT is a virtual instance of a physical system (twin) that is continually updated with the latter's performance, maintenance, and health status data throughout the physical system's life cycle (Fuller et al., 2020; Madni et al., 2019). It is the virtual and computerized counterpart of a physical system that can be used to simulate it for various purposes, exploiting a real-time synchronization of the sensed data coming from the field (Negri et al., 2017; Onaji et al., 2022).

The integration of DT, optimizes manufacturing by enhancing productivity, automation, and quality control while enabling cost reduction, waste minimization, improved safety, and sustainable practices such as cleaner production and efficient recycling (Aljuaid et al., 2024; Wang et al., 2021; Yusuf & Lytras, 2023; Zhang et al., 2022). Accordingly, manufacturing firms must embrace smart manufacturing technologies, particularly DT, to enhance their sustainable performance. As a result, Saudi Arabia, in line with Vision 2030, has implemented a comprehensive strategy to enhance its industrial sector. Key efforts include investments in infrastructure, financial incentives, and collaboration with the World Economic Forum (WEF) to advance infrastructure readiness by 50% through digitally enabled projects, supported by a USD 453 billion fund, demonstrating its commitment to innovation and sustainability (Alharbi, 2024; Efthymiou & Ponis, 2021; Mahnashi et al., 2023; Ng et al., 2022).

Although sustainable manufacturing practices and technologies like Digital Twin (DT) align with Saudi Arabia's Vision 2030, research on the impact of DT readiness on the sustainable performance of Saudi manufacturing firms remains limited (Farrukh Shahzad et al., 2025). This study addresses this gap by surveying managers to assess their perceptions of how DT readiness influences the sustainable performance of Saudi manufacturing firms.

Research problem:

Many manufacturing firms have primarily focused on leveraging Industry 4.0 technologies to enhance production and profitability, often overlooking the environmental and social implications associated with their operations (Furstenau et al., 2020; Oláh et al., 2020), which include the depletion of natural resources, environmental degradation, inequitable wealth distribution, and substandard working conditions (Bonilla et al., 2018; Oláh et al., 2020). This perspective can be partly explained by the strategic and operational difficulties encountered by manufacturing companies in adopting and maintaining effective sustainability initiatives, particularly in the context of market volatility and uncertainty (Chatterjee et al., 2022; Eldrandaly et al., 2022; Garbie, 2017; Khalid et al., 2022; Rahman et al., 2023). However, manufacturing firms are increasingly required to balance the demand for higher returns on investment with the imperative to reduce their environmental impact while creating a workplace that supports collaboration, lifelong learning and the continuous development of employee skills, fostering a more attractive and sustainable organizational environment (Machado et al., 2020; Oláh et al., 2020).

Heightened awareness of the negative consequences of manufacturing operations on the environment and society has created an urgency for manufacturing firms to adopt Sustainable Manufacturing (SM) (Garetti & Taisch, 2012; Sartal et al., 2020). To support this transition, firms develop Sustainable Manufacturing (SM) agendas and initiatives aimed at enhancing energy and material efficiency, increasing the utilization of natural, biodegradable, and recycled resources, and minimizing pollution across air, water, and soil. These efforts also seek to enhance public health and safety by mitigating associated risks, while maintaining the economic viability of production processes (Garetti & Taisch, 2012; Gunasekaran & Spalanzani, 2012; Haapala et al., 2013; Posinasetti, 2013). In other words, SM is aimed at improving the economic, environmental, and social performance of a firm; widely known as the Triple Bottom Line (TBL) or sustainable performance (Elkington, 1998; Haapala et al., 2013; Machado et al., 2020). Sustainable performance can be defined as the harmonization of financial, social, and environmental purposes in the delivery of fundamental business actions to maximize value. It is the performance of a corporation in all dimensions as well as for all drivers of corporate sustainability (Hossin et al., 2021; Patil et al., 2024; Sebhatu, 2009).

Industry 4.0 technologies, especially Digital Twin (DT) systems, are set to transform the manufacturing landscape by embedding sophisticated digital innovations that promote enhanced productivity and more efficient use of resources (Kamble et al., 2022; Sharma et al., 2021). According to Stock and Seliger (2016) and Sharma et al. (2021), Industry 4.0 presents substantial potential for advancing sustainable value creation within industrial sectors, particularly through the lens of the TBL framework. Digital Twin (DT) technology supports sustainable development in manufacturing by improving efficiency, reducing waste and energy consumption, enhancing stakeholder collaboration, and creating inclusive job opportunities (particularly for individuals with IT skills, the elderly, and people with disabilities), while also enhancing the quality of the working environment through the reduction of repetitive tasks and the promotion of more meaningful roles (Furstenau et al., 2020; Machado et al., 2020; Sharma et al., 2021). Previous studies also concluded that Industry 4.0 technologies, such as DT, can help manufacturers manage their supply chains and achieve better organizational results by enabling them to deal with erratic environmental changes (Kumar & Bhatia, 2021; Sharma et al., 2023). According to Rodríguez-Espíndola et al. (2022), industry 4.0 boosts productivity in unstable markets by providing supply chain resilience, innovation, fast adaptation, and sustainability. Accordingly, A firm’s capability to integrate industry 4.0 technologies, such as DT, into its operations can significantly enhance resource efficiency and environmental performance (Farrukh Shahzad et al., 2025; Yavuz et al., 2023).

Previous studies claimed that without technical innovation and readiness, sustainable performance is not conceivable (Ali & Johl, 2023; Lodhi et al., 2024; Rajput & Singh, 2019). Also, according to Farrukh Shahzad et al. (2025) and Karmaker et al. (2023), the digital transformation of manufacturing industries is largely propelled by their level of technological readiness and capacity for innovation. Furthermore, digitalization transforms organizations from traditional to advanced business models and pushes them to shift towards more sustainable practices in the market (Deshmukh & Haleem, 2020; Farrukh

Shahzad et al., 2025; Ghobakhloo et al., 2021). Therefore, investing in digital readiness can facilitate industry 4.0 implementation, thus enhancing sustainable performance (Farrukh Shahzad et al., 2025).

Manufacturing firms equipped for Digital Twin (DT) deployment are able to optimize energy and resource utilization, minimize carbon emissions and waste, and thereby enhance their overall sustainability performance (Patil et al., 2024; Zhang et al., 2024). As noted by Patil et al. (2024), DT readiness involves a combination of technological, organizational, and strategic preparedness necessary for the successful implementation and utilization of DT systems. This readiness supports effective DT deployment, which enhances information flow, enables real-time monitoring, and facilitates predictive analytics, thereby allowing organizations to respond adaptively to changing environmental conditions. Consequently, Patil et al. (2024) identified four key dimensions that define DT readiness: Technological Readiness (TR), Organizational Readiness and Support (ORS), Perceived Values and Benefits (PVB), and Data Readiness (DR).

The limited research on the impact of DT readiness on sustainable performance arises from an insufficient understanding of this relationship within manufacturing companies (Farrukh Shahzad et al., 2025). In Saudi Arabia, the relationship between Digital Twin (DT) readiness and the sustainable performance of manufacturing firms remains underexplored, despite the central role of sustainability, Industry 4.0 technologies, and industrial development in Vision 2030. This study seeks to bridge this gap by examining how managers of Saudi manufacturing firms perceive the impact of DT readiness on sustainable performance. Consequently, the research problem is framed through the following primary research question:

"***What is the impact of Digital Twins' Readiness (DTR) on the Sustainable Performance (SP) of Saudi manufacturing firms?***"

Examining the following sub-questions can provide meaningful insights into addressing the main research question:

1- What is the impact of Technological and Data Readiness (TDR) on the Sustainable Performance (SP) dimensions of Saudi manufacturing firms?

2- What is the impact of Organizational Readiness and Support (ORS) on the Sustainable Performance (SP) dimensions of Saudi manufacturing firms?
3- What is the impact of Perceived Values and Benefits (PVB) on the Sustainable Performance (SP) dimensions of Saudi manufacturing firms?

Research objective:

This study seeks to survey managers in Saudi manufacturing firms to capture their perspectives on the influence of Digital Twins' Readiness (DTR) (TDR, ORS, and PVB) on the Sustainable Performance (SP) of Saudi manufacturing firms. This entails:

1- Studying the impact of Technological and Data Readiness (TDR) on the Sustainable Performance (SP) dimensions of Saudi manufacturing firms.
2- Examining the impact of Organizational Readiness and Support (ORS) on the Sustainable Performance (SP) dimensions of Saudi manufacturing firms.
3- Analyzing the impact of Perceived Values and Benefits (PVB) on the Sustainable Performance (SP) dimensions of Saudi manufacturing firms.

Literature review and hypothesis development:

This section reviews the literature on the impact of Digital Twins' Readiness (DTR) on Sustainable Performance (SP). While most studies report a positive and significant impact of DTR on SP (Farrukh Shahzad et al., 2025; Patil et al., 2024; Ullah et al., 2024; Yavuz et al., 2023), some research indicates no significant effect (Ali & Johl, 2023), leading to inconclusive findings in the existing literature. Furthermore, some research reported that DTR mediates the relationship between strategic orientation and sustainable competitiveness (Ed-Dafali et al., 2023).

Patil et al. (2024) examined the effect of DT readiness on the sustainable performance of manufacturing firms in India. The study collected data from 754 manufacturers, before analyzing it using Structural Equation Modelling (SEM). Findings revealed that DT readiness has a significant positive impact on the sustainable performance of manufacturing firms. Similarly, Farrukh Shahzad et al. (2025) analyzed the impact of Industry 4.0 readiness on the sustainable performance of food manufacturing firms in Pakistan. The study collected data from 318 employees from food manufacturing firms. The data was then analyzed using SEM. The results showed that Industry 4.0 readiness has a significant positive impact the sustainable performance of food manufacturing firms in Pakistan. Furthermore, Yavuz et al. (2023) investigated the influence of Industry 4.0 readiness on sustainable performance by conducting a survey of 302 participants in Turkey. Using SEM, the study found that Industry 4.0 readiness positively and significantly influences sustainable performance.

Correspondingly, Ullah et al. (2024) surveyed 1660 managerial employees from 418 manufacturing firms to analyze how technology readiness affect sustainable performance of manufacturing firms in Pakistan. Using SEM, the study concluded that technology readiness positively and significantly impacts sustainable performance. Also, Ed-Dafali et al. (2023) used SEM to analyze data collected from 144 SMEs in emerging markets. They found that Industry 4.0 readiness mediates the relationship between strategic orientation and sustainable competitiveness.

Other studies have investigated how Industry 4.0/technology readiness affects sustainable performance. For instance, Ali and Johl (2023) investigated how industry 4.0 readiness affects sustainable manufacturing practices by surveying 228 senior managers of manufacturing SMEs in China. The study concluded that Industry 4.0 readiness had a positive yet non-significant impact on sustainable manufacturing practices. Rakic et al. (2021) emphasized that readiness for Industry 4.0 serves as a fundamental prerequisite for achieving sustainability. Their research focused on evaluating the industry 4.0 readiness levels of Serbian manufacturing firms, revealing that over a three-year period, these firms advanced from a stage of non-adoption to basic readiness. This progression signifies a critical step toward fostering a more sustainable industrial landscape. Ullah et al. (2024) also investigated the relationship between technological readiness and sustainability performance by analyzing data collected from 1,660 managerial employees within manufacturing firms. Utilizing SEM, their study confirmed that technological readiness exerts a significant and positive influence on sustainability performance. Ultimately, Qureshi et al. (2023) found out that the application of Advanced Manufacturing Technologies (AMT), such as Computer-Aided Design (CAD) and Computer-Aided Machining (CAM), Automated Guide Vehicles (AGV), robotics, and machine networking, has a significant positive impact on Industry 4.0 readiness.

Existing research predominantly supports the significant positive impact of industry 4.0 or Digital Twins' Readiness (DTR) on Sustainable Performance (SP), though some studies have reported a positive but non-significant relationship. These investigations have been drawn from diverse geographical contexts, including India, Pakistan, China, and Turkey. However, research examining this relationship within the Saudi Arabian manufacturing sector remains limited. To address this gap, the present study aims to contribute to the existing body of knowledge by investigating the influence of DTR on SP in Saudi manufacturing firms. Based on the reviewed literature, the following research hypotheses are proposed:

"H_1: Technological and Data Readiness (TDR) has a significant impact on the Economic Performance (EcP) of Saudi manufacturing firms."

"H_2: Technological and Data Readiness (TDR) has a significant impact on the Social Performance (SoP) of Saudi manufacturing firms."

"H_3: Technological and Data Readiness (TDR) has a significant impact on the Environmental Performance (EnP) of Saudi manufacturing firms."

"H_4: Organizational Readiness and Support (ORS) has a significant impact on the Economic Performance (EP) of Saudi manufacturing firms."

"H_5: Organizational Readiness and Support (ORS) has a significant impact on the Social Performance (SP) of Saudi manufacturing firms."

"H_6: Organizational Readiness and Support (ORS) has a significant impact on the Environmental Performance (EnP) of Saudi manufacturing firms."

"H_7: Perceived Values and Benefits (PVB) has a significant impact on the Economic Performance (EcP) of Saudi manufacturing firms."

"H_8: Perceived Values and Benefits (PVB) has a significant impact on the Social Performance (EcP) of Saudi manufacturing firms."

"H_9: Perceived Values and Benefits (PVB) has a significant impact on the Environmental Performance (EcP) of Saudi manufacturing firms."

Research importance:

The influence of Digital Twins' Readiness (DTR) on the Sustainable Performance (SP) of manufacturing firms remains insufficiently examined within the Saudi context. This study seeks to fill this research gap by analyzing the impact of DTR on SP in Saudi manufacturing firms. While prior studies suggest a generally positive relationship between DTR and SP across various industries, its specific effects in Saudi Arabia remain unclear. By offering empirical insights tailored to the Saudi manufacturing sector, this research aims to enhance understanding of DTR's role in driving sustainability and inform strategic industrial advancements.

This research underscores the importance of integrating advanced technologies into Saudi Arabia's manufacturing sector to align with Vision 2030's sustainability objectives. Developing Digital Twins' Readiness (DTR) requires not only enhancing employees' technical competencies but also fostering an innovation-driven work environment. The study's findings offer valuable insights for industry leaders, enabling them to design effective implementation strategies that optimize Sustainable Performance (SP) and contribute to the long-term resilience and competitiveness of the manufacturing industry.

Additionally, the study underscores the importance of investing in digital infrastructure, promoting cross-industry collaboration, and establishing regulatory frameworks that support the adoption of DT technology. Policymakers can leverage these insights to develop initiatives that facilitate a smoother transition to smart manufacturing, while organizations can use them to optimize resource efficiency, improve operational agility, and enhance overall competitiveness in the global market.

Theoretical framework:

This section presents the conceptual framework of the study, providing theoretical insights into the core research variables to facilitate a comprehensive understanding of the research problem and the interrelationships among these variables. The discussion is structured around four central themes: Digital Twins (DT), Digital Twin Readiness (DTR), Sustainable Performance (SP), and the impact of DTR on SP.

Digital Twins: Background, Definitions, and Types

The concept of the Digital Twin (DT) is credited to Michael Grieves, in collaboration with John Vickers of NASA. Grieves first introduced the idea during a 2003 lecture on product life-cycle management at the University of Michigan (Grieves, 2014; Grieves & Vickers, 2017; Singh et al., 2021). Since its inception, the concept of the Digital Twin (DT) has undergone significant evolution and refinement through continuous technological advancements and expanding application domains. Figure 2 illustrates the chronological development of terminology associated with the evolution of the Digital Twin (DT) concept.

Initially, DT was defined as a virtual counterpart of a physical product that integrates detailed information about the product, emerging from the field of product life-cycle management. The concept subsequently advanced into the notion of "Mirrored Spaces Model", incorporating three fundamental components: the physical product, its virtual counterpart, and the bi-directional data exchanges that facilitate the flow of real-time data from the physical entity to its digital representation, as well as the transmission of insights, processes, or control actions from the digital model back to the physical system (Grieves, 2014; Grieves & Vickers, 2017; Jones et al., 2020). In 1991, David Gelernter envisioned a related concept termed "Mirror Worlds", wherein software-based models replicate real-world systems by processing information derived from the physical environment (Gelernter, 1993).

By 2006, the conceptual framework initially introduced by Grieves underwent a terminological revision, transitioning from the "Mirrored Spaces Model" to the "Information Mirroring Model" (Grieves, 2014; Grieves & Vickers, 2017). This revised model emphasized the bidirectional nature of the connection between the physical and virtual spaces and introduced the concept of multiple virtual spaces corresponding to a single physical entity, enabling the exploration of alternative designs or concepts within the digital environment, as shown in Figure 1.

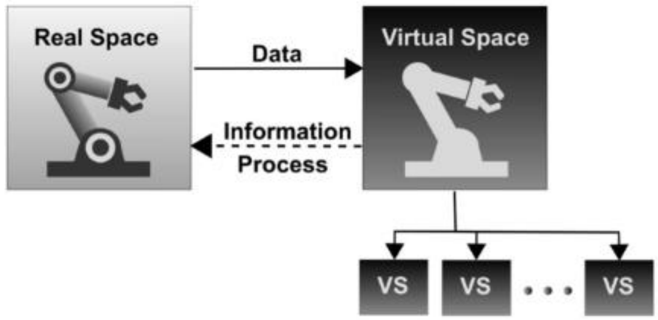

Figure 1 Information mirroring model (Singh et al., 2021)

The term "Digital Twin (DT)" was first formally introduced in NASA's draft version of the technological roadmap in 2010 (Shafto et al., 2010), where it was described as:

"*An integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin*" (Boschert & Rosen, 2016; Rosen et al., 2015)

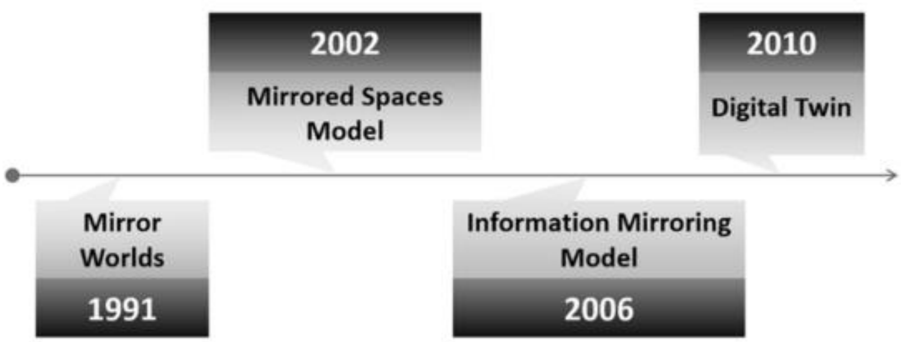

Figure 2 Chronological Development of Digital Twin (DT) (Singh et al., 2021)

Since that time, the definition and conceptual understanding of Digital Twin (DT) have been extensively explored and elaborated upon within the literature. Some researchers believed that the two most widely accepted definitions of DT were those given by Grieves (2014) (a virtual, digital equivalent to a physical product) and NASA. However, according to Ren et al. (2025), a widely accepted definition of DT is as follows:

"*A DT is a reference model designed to facilitate the convergence of physical and virtual spaces. This concept involves the integration of a physical entity with a high-fidelity digital replica, both of which operate in tandem throughout a product's lifecycle or a given process. Central to the Digital Twin paradigm is the real-time interaction, communication, and collaboration between the physical domain and its corresponding cyberspace environment*".

Beyond these, the literature offers numerous alternative definitions of Digital Twin (DT), all converging on the core idea that it serves as a digital replica of processes, real world objects, physical manufacturing systems, or physical entities (e.g., factories, machines, or workers) (Kaewunruen & Lian, 2019; J. Liu et al., 2019; Söderberg et al., 2017). For instance, Rosen et al. (2015) asserted that DTs are highly accurate representations of a process's current state, capturing its behavior and interactions within real-world environments. Similarly, Schluse and Rossmann (2016) and Nikolakis et al. (2019) defined DTs as virtual counterparts of real-world objects that include both digital representations and communication functionalities, enabling them to function as intelligent nodes within the Internet of Things (IoT) and Services. Likewise, Leng et al. (2019) described DT as an accurate and real-time digital replica of a physical manufacturing system, fully reflecting all of its operational functionalities. Brenner and Hummel (2017) and Schluse et al. (2018) also described DT as a digital replica of physical entities such as factories, machines, or workers, which can be independently expanded, automatically updated, and accessed globally in real time. He et al. (2018) defined DT as a dynamic digital representation of physical assets, processes, and systems that enable comprehensive monitoring throughout their entire life cycle. According to Fotland et al. (2020), a DT is a digital replica of a physical asset that gathers real-time data from the asset and generates insights, including those not directly measurable through physical hardware.

Bruynseels et al. (2018) and P. Wang et al. (2019) emphasized that DTs represent a paradigm in which selected real-time measurements are continuously integrated into simulation models, allowing the digital environment to dynamically inform and adaptively guide the physical world in return. Madni et al. (2019) and Q. Liu et al. (2019) described DT as a virtual instance of a physical system (twin) that is continually updated with the latter's performance, maintenance, and health status data throughout the physical system's life cycle. Luo et al. (2019) argued that DT is a multi-domain, ultra-high-fidelity digital model that integrates various disciplines, including mechanical, electrical, hydraulic, and control systems. Additionally, J. Wang et al. (2019) defined DT as a distinctive, dynamic model of a physical system, enabled by a range of advanced technologies such as multi-physics simulation, machine learning, augmented and virtual reality, and cloud computing services.

In line with the diversity of definitions, DTs can also be categorized into distinct types based on various criteria, including the point of creation, degree of integration, functional applications, hierarchical structure, and stage of maturity. Based on the stage of creation within a product's life cycle, Digital Twins (DTs) can be classified into two types: (1) the Digital Twin Instance (DTI), developed during the design phase prior to prototype fabrication, and (2) the Digital Twin Prototype (DTP), generated during the production phase once the physical product is finalized (Botín-Sanabria et al., 2022; Grieves, 2014; Grieves & Vickers, 2017; Hribernik et al., 2013; Ríos et al., 2015; Singh et al., 2021; Wuest et al., 2015). According to the level of integration, Digital Twins (DTs) can be categorized as follows: (1) a Digital Model, which lacks automatic data exchange or influence between the physical and virtual systems; (2) a Digital Shadow, where data flows automatically and unidirectionally from the physical system to its digital counterpart; and (3) a Digital Twin, characterized by bidirectional interaction, allowing dynamic data exchange and mutual influence between the physical and virtual environments (Fuller et al., 2020; Hribernik et al., 2013; Kritzinger et al., 2018; Shafto et al., 2010). Figure 3 compares digital models, shadows, and twins.

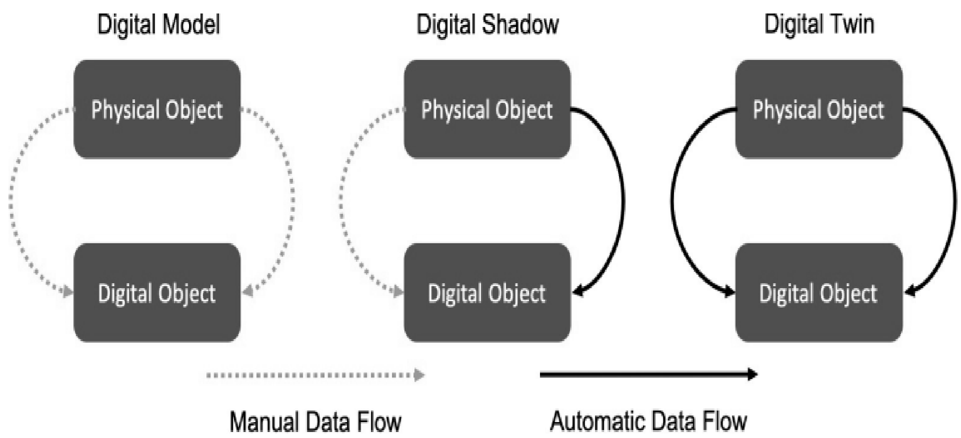

Figure 3 A comparison between Digital model, shadow, and twin (Fuller et al., 2020; Kritzinger et al., 2018)

From an application perspective, DT can be either a: (1) Product DT, employed for product prototyping; (2) Process DT, used to validate and optimize processes; and (3) Performance DT, used for decision-making purposes. Digital Twins (DTs) can be organized hierarchically into three levels: unit level (individual components), system level (integrated units such as a production line), and system of systems (SoS) level, which connects multiple systems to represent large-scale, complex operations (Negri et al., 2017; Ren et al., 2025; Singh et al., 2021; Zhang et al., 2024). DTs can be categorized by their data sophistication into three types: (1) Partial DTs, which use limited data; (2) Clone DTs, which include all essential data for prototyping and development; and (3) Augmented DTs, which combine real-time and historical data with analytics to generate deeper insights (Madni et al., 2019; Singh et al., 2021). However, Madni et al. (2019) proposed that DT maturity is determined not only by data integration but also by the sophistication of the virtual model. They classified DTs into four levels: Level I (Pre-DT), a generic model used before the physical asset exists to support design decisions; Level II (DT), which incorporates real-time, bidirectional data for monitoring and maintenance; Level III (Adaptive DT), which uses supervised learning and adaptive interfaces to support real-time decision-making; and Level IV (Intelligent DT), which leverages unsupervised and reinforcement learning for autonomous system optimization and advanced analytics.

Digital Twins' Readiness (DTR) and its dimensions:

Readiness is the state of being fully prepared for something (Pacchini et al., 2019). Relatedly, Industry 4.0 readiness refers to the extent to which organizations are equipped to adopt and effectively utilize Industry 4.0 technologies to enhance their operations and competitiveness (Hizam-Hanafiah et al., 2020; Stentoft et al., 2019). In other words, it reflects the level of digital preparedness within companies to adopt, implement, and benefit from Industry 4.0 technologies (Hizam-Hanafiah et al., 2020; Schwab, 2021; Vazire, 2018).

The dimensions of Industry 4.0 readiness encompass several critical factors, including the pressure to transform existing processes, a willingness to take risks associated with emerging technologies, adequate knowledge of those technologies, a workforce equipped with the necessary skills and motivation, and strong top management support both in terms of financial investment and a positive attitude toward technological change (Haug et al., 2011; Stentoft et al., 2019). A lack of readiness is recognized as a key factor contributing to the failure of Industry 4.0 implementations. Therefore, the higher the level of readiness within a company, the greater its ability to effectively adopt and utilize relevant technologies to support its business objectives (Ali & Miller, 2017; Stentoft et al., 2019).

Based on these dimensions, among others, Rakic et al. (2021) classified manufacturing firms into six levels based on their Industry 4.0 readiness, as depicted in Figure 4. Firms at Level 0 are considered non-users, those at Levels 1 – 3 exhibit basic readiness, and Levels 4 – 5 indicate high readiness for Industry 4.0:

1- <u>Level 0</u>: includes companies with traditional processes that do not utilize digital technologies.
2- <u>Level 1</u>: refers to firms using digital processes in one of three key technological domains.
3- <u>Level 2</u>: involves usage in two domains.
4- <u>Level 3</u>: represents companies engaged in all three domains, incorporating both IT- and CPS-related processes.
5- <u>Level 4</u>: Comprises firms using all technology fields and at least two CPS-related technologies.

6- Level 5: includes those employed in all fields and at least three CPS-related technologies.

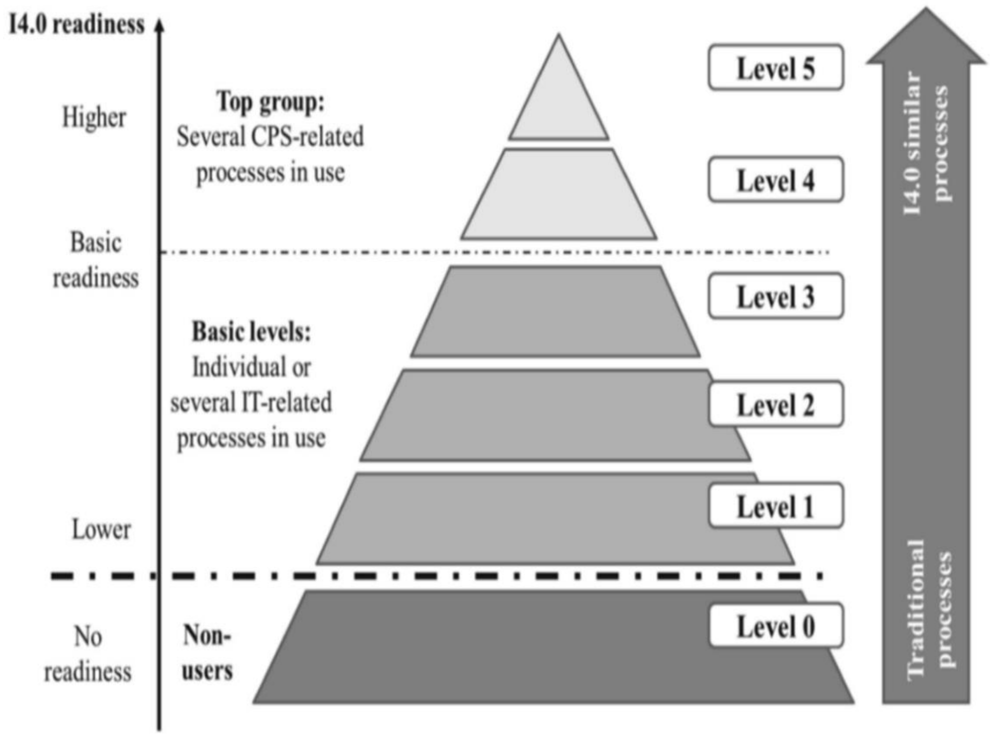

Figure 4 Levels of industry 4.0 readiness (Rakic et al., 2021)

As a component of Industry 4.0 readiness, Digital Twin Readiness (DTR) refers to the level of technological preparedness required for the effective implementation and deployment of Digital Twins (DT) across manufacturing processes. It involves the technological, organizational, and strategic capabilities necessary to successfully implement and utilize DT systems within an organization. According to Barykin et al. (2021), DTR entails possessing the essential technological infrastructure, robust data integration mechanisms, analytical competencies, and organizational coherence needed to design, implement, and extract valuable insights from DT applications. DTR is acknowledged for its ability to improve real-time data acquisition, analysis, and informed decision-making throughout operational activities (Alnaser et al., 2024; Attaran & Celik, 2023; Patil et al., 2024; Riedelsheimer et al., 2020).

Several studies have outlined various dimensions of DTR. For instance, Alnaser et al. (2024) identified seven key dimensions: organizational support and preparedness, technological infrastructure, data privacy, security and regulatory compliance, knowledge, expertise and workforce competencies, financial factors, external market influences, and sustainability-related considerations. Similarly, Patil et al. (2024) selected four main dimensions of DTR: Technological Readiness (TR), Organizational Readiness and Support (ORS), Perceived Values and Benefits (PVB), and Data Readiness (DR). This study adopts the framework proposed by Patil et al. (2024) for evaluating DTR. The following sections provide a detailed examination of each DTR dimension:

1- **Technological Readiness (TR):** TR denotes the extent to which an organization or system is equipped to successfully adopt, integrate, and utilize new technologies within its operational framework. It includes the capability to manage technological change, exploit innovation-driven opportunities, and apply the required infrastructure, expertise, and strategic planning to effectively implement and benefit from emerging digital solutions (Hastig & Sodhi, 2020; Patil et al., 2024). TR establishes the foundational capabilities necessary for digital transformation, whereas DTR builds upon this foundation to foster innovation and enhance operational performance through sophisticated digital modeling, simulation, and analytical techniques (Patil et al., 2024; Wang et al., 2021).

2- **Organizational Readiness and Support (ORS):** ORS reflects an organization's overall capacity and willingness to adopt and implement innovations or emerging technologies. It includes critical elements such as infrastructure, organizational culture, resource availability, workforce competencies, and adaptable processes that collectively influence the organization's responsiveness to change. A high degree of ORS indicates strong preparedness and motivation to pursue transformative initiatives. Additionally, leadership support signifies the proactive involvement, strategic guidance, and sustained commitment of top management in facilitating and championing such efforts (Chardine-Baumann & Botta-Genoulaz, 2014; Patil et al., 2024)

3- **Perceived Values and Benefits (PVB):** PVB represents the subjective evaluation by individuals or organizations of the overall worth and appeal of a product, service, or concept. This evaluation involves weighing the anticipated benefits against the associated costs, considering not only financial aspects but also emotional, functional, and experiential factors. PV significantly influences stakeholders' attitudes, preferences, and decision-making processes, determining their inclination to adopt or invest in a particular solution. In contrast, benefits refer to the tangible and intangible advantages gained from utilization, such as improved efficiency, cost reductions, enhanced performance, better decision-making, innovation opportunities, and increased competitive advantage (Jones et al., 2020; Patil et al., 2024).

4- **Data Readiness (DR):** DR reflects the extent to which an organization's data is well-structured, easily accessible, accurate, complete, and of sufficient quality to enable effective decision-making, analysis, and the implementation of technologies. It entails the preparation and organization of data resources to ensure they are relevant, dependable, and available for both operational and analytical use. As a foundational element for adopting emerging technologies, DR plays a crucial role, since the reliability and availability of data directly influence the success and value of such technological initiatives (Patil et al., 2024).

Sustainable Performance (SP):

The concept of sustainability was first formally introduced in the 1987 Brundtland Report, which defined it as the ability to meet the needs of the present generation without compromising the capacity of future generations to meet their own needs (Arena et al., 2009; Hahn & Figge, 2011). Subsequently, Elkington (1998) introduced the concept of "corporate sustainability" defining it as a broadened corporate outlook that incorporates environmental, social, and economic dimensions, as depicted in . Corporate sustainability involves broadening the traditional financial focus to a TBL approach that also considers a company's environmental and social performance (Albertini, 2013; Alshehhi et al., 2018).

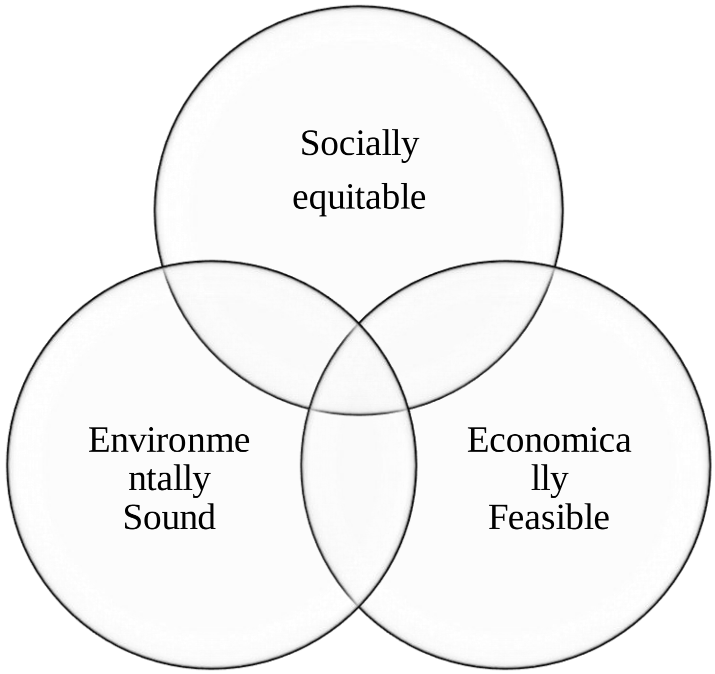

Figure 5 The Triple Bottom Line (TBL) (Elkington, 1998)

Today, industrial performance indicators are evolving from purely economic measures toward those that emphasize sustainability (Abdul-Rashid et al., 2017). Environmental performance focuses on reducing emissions and resource consumption through cleaner energy, economic performance emphasizes growth while safeguarding the environment, and social performance ensures industries support societal well-being and avoid causing social harm (Abdul-Rashid et al., 2017; Yusuf & Lytras, 2023; Yusuf et al., 2013).

Sustainable performance, a concept that followed the introduction of sustainable development, reflects the combined assessment of economic, environmental, and social outcomes associated with a particular practice (Chardine-Baumann & Botta-Genoulaz, 2014). Defined as the ability to operate responsibly across environmental, social, and economic dimensions (P. Wang et al., 2019), sustainable performance is particularly critical in the manufacturing industry. Sustainable practices in manufacturing reduce ecological impacts, build consumer trust, and ensure compliance with increasingly stringent environmental regulations (Ding et al., 2022; Islam et al., 2021; Le, 2023). The objective of having a sustainable organization is the ultimate goal for manufacturing organizations due to the attractiveness of the positive impact on the environment, society, and economy (Ghaithan et al., 2023). Sustainable manufacturing practices focus on the production of products that are cost-effective and reduce negative environmental effects while preserving resources. Manufacturing firms must demonstrate a strong vision to the environment and society in their operations as a result of the change demanded by the community to emphasize economic activity repercussions (Aboelmaged, 2018; Jayal et al., 2010).

The relationship between Digital Twins' Readiness (DTR) and Sustainable Performance (SP):

Organizations can greatly increase their sustainable performance by combining the implementation of industry 4.0 technology, such as DT, with solid technical preparedness (Farrukh Shahzad et al., 2025; Ghobakhloo et al., 2021). According to Hosta and Zabkar (2021), sustainable manufacturing firms are better equipped to adapt to changing market conditions and consumer preferences, ensuring their viability and contributing to a resilient future for the planet. Similarly, Stock and Seliger (2016) asserted that industry 4.0 offers significant opportunities for achieving sustainable manufacturing through the pervasive use of Information Technology (IT) infrastructure. Furthermore, Buhaya and Metwally (2024) argued that digital technologies also offer effective tools for designing, manufacturing, and maintaining eco-friendly products that minimize harmful emissions and reduce the use of natural resources across their life cycle. As illustrated in Figure 6, The 6R concept (i.e., reducing, reusing, recycling, redesigning, recovering, and remanufacturing) can be effectively supported by digital technologies to enhance sustainable performance in manufacturing firms.

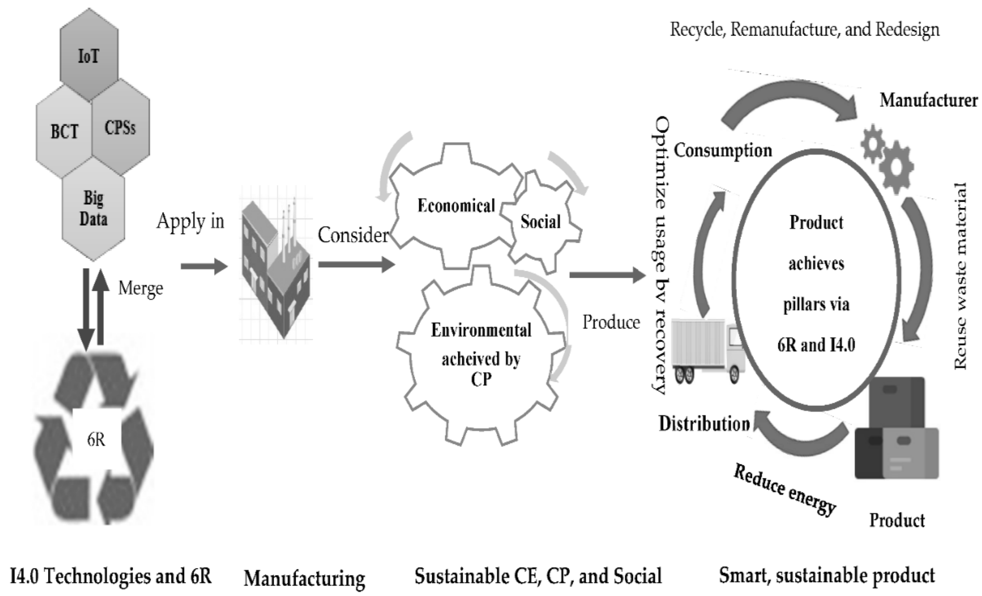

Figure 6 The role of industry 4.0 technologies in the sustainability of manufacturing firms (Eldrandaly et al., 2022).

Industry 4.0 technologies offer significant potential for generating sustainable value across economic, environmental, and social dimensions by enhancing the efficiency of resource utilization (Lopes de Sousa Jabbour et al., 2018). These technologies, including DT, contribute to sustainable development by improving decision-making, enhancing operational performance, reducing costs and lead times, and enabling the production of high-quality goods more efficiently, ultimately boosting overall business performance (Jayashree et al., 2021; Ma et al., 2023). They also help monitor carbon emissions and eco-efficiency, reduce energy use and waste, promote energy conservation, and support resource reuse and recycling to optimize overall resource efficiency (Kumar & Bhatia, 2021; Li et al., 2020). Socially, Industry 4.0 technologies enhance employee satisfaction, strengthen stakeholder relationships, improve retention, promote a positive brand image, raise social responsibility awareness, and support talent attraction and innovation, collectively boosting a company's sustainability performance (Khurshid & Darzi, 2016; Mehta & Chugan, 2015; Wagner, 2013).

Buhaya and Metwally (2024) and Li et al. (2020) also highlighted that those digital technologies present both opportunities and challenges in advancing sustainable performance within manufacturing. These technologies can drive improvements in product innovation, operational efficiency, and supply chain resilience, while also boosting customer satisfaction. Furthermore, they facilitate better resource allocation, which may lead to substantial gains in sustainable performance. Nonetheless, the adoption of these technologies may intensify competition and pose financial as well as environmental challenges for manufacturers. Therefore, it is essential to further investigate the influence of digital technologies, such as DT, on sustainable performance, especially within the context of developing countries, to fully grasp their wider implications.

Correspondingly, Lai et al. (2015) and Addo-Tenkorang and Helo (2016), manufacturing processes and sustainable performance are closely linked to effective Supply Chain Management (SCM), which relies on high-quality information to ensure operational efficiency and environmental responsibility. Digital technologies enhance a company’s ability to manage and analyze data, facilitating informed decision-making for operational efficiency and environmental sustainability, streamlined production planning, cost reduction, and improved profitability.

Furthermore, the key objective of Industry 4.0 technologies, such as DT, is to increase the productivity of an organization through a high level of automation (El Baz et al., 2022; Hahn, 2020). Firms have assessed the adoption of Industry 4.0 technologies, such as DT, to simplify their manufacturing processes to enhance sustainable performance (Li et al., 2021). These technologies are also helpful in reducing greenhouse emissions and waste; they facilitate advanced tracking and monitoring systems that support companies to perform more efficiently from the ecosystem perspective. From a social angle, these technologies improve the knowledge level of employees and provide a safer working environment for staff (Soldatos et al., 2022).

Specifically, Digital Twins (DT) provide supply chain stakeholders with real-time data access, bridging the digital and physical components of operations. This connectivity enhances supply chain resilience by reducing shipment losses, damage, and fulfillment errors. Consequently, production disruptions are minimized, positively influencing both the social and economic dimensions of sustainability (Eldrandaly et al., 2022; Manupati et al., 2022; Min, 2019). According to Kamble et al. (2022), DT holds significant potential for sustainable manufacturing operations due to its data-rich environment, which enables real-time monitoring, simulation, and prediction of manufacturing processes. Furthermore, by simulating manufacturing processes, DT contribute to sustainable development and circularity by evaluating resource efficiency, recovering valuable secondary materials, and achieving energy savings (Bartie et al., 2021; Leiden et al., 2021). Vehicular DT that enable data collection, processing, and analytics can help reduce accidents and contribute to creating a safer workplace environment (Almeaibed et al., 2021). DT leveraging data fusion principles can be highly effective in reducing ambiguity and uncertainty when evaluating sustainable design alternatives (Kamble et al., 2022). Similarly, Digital Twin models are employed to conduct environmental risk evaluations and assess pollution impacts (Kamble et al., 2022). Ultimately, the use of DT throughout the entire lifecycle enhances information sharing, streamlines technical communication, improves design quality, minimizes design errors, boosts energy efficiency, supports rapid implementation, and contributes to the reduction of carbon footprints (Kaewunruen & Lian, 2019; Kaewunruen et al., 2018; Kaewunruen & Xu, 2018).

Field study:

This study investigates the perceptions of managers within Saudi manufacturing firms regarding the extent to which Digital Twins' Readiness (DTR) influences Sustainable Performance (SP). The research begins by detailing the methodological approach employed to examine the proposed hypotheses, followed by a comprehensive analysis of the results obtained from hypothesis testing.

Research methodology:

Research methodology encompasses the structured processes and techniques utilized to investigate research problems systematically. It serves as the scientific foundation for conducting research, guiding the selection of appropriate methods for data collection, analysis, and interpretation. Essentially, it provides a framework that enables researchers to describe, analyze, and predict various phenomena with accuracy and reliability (Goundar, 2012; Opoku et al., 2016; Patel & Patel, 2019). This section provides an in-depth overview of the methodological framework designed to evaluate research hypotheses. It elaborates on the sources of data, the definitions and classifications of variables, and the measurement scales utilized. Furthermore, it describes the procedures for data collection, specifies the study's target population and sampling approach, and details the statistical methods implemented for data analysis.

Research approach and data sources:

This study employed a quantitative research approach based on deductive reasoning. Deductive inferencing begins with a generalization (i.e., a theoretical framework) and then examines observations to see if they support the generalization (i.e., using confirmatory techniques to confirm the theoretical model) (Hall et al., 2023).

Data is generally categorized into primary and secondary sources. Primary data consists of firsthand information collected directly by researchers through methods such as interviews, surveys, or experiments. This type of data is original and tailored to the specific objectives of a study. Conversely, secondary data refers to pre-existing information that has been gathered and documented by other researchers or organizations. Examples include published books, academic journal articles, and government reports, which provide valuable insights for further analysis and interpretation (Ajayi, 2017; Mwita, 2022; Rabianski, 2003).

The study utilized a survey as its primary data collection method, focusing on managers of Saudi manufacturing firms to explore their perceptions of the relationship between Digital Twins' Readiness (DTR) and the Sustainable Performance (SP) of Saudi enterprises. Secondary data were obtained from scholarly sources, including academic books, journal articles, and dissertations.

Research variables and related measures:

This research investigates the impact of Digital Twins' Readiness (DTR) on the Sustainable Performance (SP) of Saudi enterprises. Drawing on the framework established by Patil et al. (2024), DTR is assessed through three dimensions: Technological and Data Readiness (TDR), Organizational Readiness and Support (ORS), and Perceived Values and Benefits (PVB). SP is also evaluated using three dimensions: Economic Performance (EcP), Social Performance (SoP), and Environmental Performance (EnP). A summary of the research variables and their corresponding measurement indicators is presented in Table 1.

1- Digital Twins' Readiness [$DTR\,(x)$]: DTR measures an organization's ability to develop and implement Digital Twin (DT) solutions effectively. It serves as the primary independent variable in the study. This research evaluates DTR using three core dimensions identified by Patil et al. (2024), which are:
   a) Technological and Data Readiness [$TR\,(x_1)$]: TDR evaluates the capability of Saudi enterprises to successfully adopt, implement, and integrate emerging technologies into its operational and strategic processes. It also examines the quality, organization, accessibility, and completeness of data within Saudi enterprises. TDR is evaluated based on three items adapted from Patil et al. (2024), Yu et al. (2022), and Attaran and Celik (2023).
   b) Organizational Readiness and Support [$ORS\,(x_2)$]: ORS evaluates the ability of Saudi enterprises to adopt and integrate innovations, technological advancements, and organizational changes effectively. It also examines the extent to which leadership actively supports, guides, and commits to these initiatives, ensuring their successful implementation. ORS is evaluated based on three items adapted from Patil et al. (2024) and Dubey (2023).
   c) Perceived Values and Benefits [$PVB\,(x_3)$]: PVB measures how individuals within Saudi enterprises perceive the relevance, benefits, and overall worth of Digital Twin (DT) technology. PVB is evaluated based on three items adapted from Patil et al. (2024) and Voipio et al. (2023).
      2- Sustainable Performance [($SP\,(y)$]: SP assesses the overall performance of Saudi enterprises by integrating economic, social, and environmental dimensions. It reflects an organization's ability to

achieve long-term profitability while maintaining social responsibility and minimizing environmental impact. SP is measured using three dimensions, which are:

a) Economic Performance [$EcP\ (y_1)$]: EcP measures how digital twins technology affects the economic performance of Saudi manufacturing firms. It is evaluated based on three items adapted from Patil et al. (2024) and Harikannan et al. (2025).
b) Social Performance [$SoP\ (y_2)$]: SoP evaluates how Saudi enterprises affects the economic performance of Saudi manufacturing firms. SoP is evaluated based on three items adapted from Patil et al. (2024) and Harikannan et al. (2025).
c) Environmental Performance [$EnP\ (y_3)$]: EnP describes the effects on digital twin readiness on the environmental performanc4e of Saudi manufacturing firms. EnP is evaluated based on three items adapted from Patil et al. (2024) and Harikannan et al. (2025).

Table 1 Research variables and corresponding measurement scales

Construct	Dimensions	Items	Evidence
Digital Twins' Readiness (DTR)	TDR	3 items (1 – 3)	Patil et al. (2024) Yu et al. (2022) Attaran and Celik (2023)
	ORS	3 items (4 – 6)	Patil et al. (2024) Dubey (2023)
	PVB	3 items (7 – 9)	Patil et al. (2024) Voipio et al. (2023)
Sustainable Performance (SP)	EcP	3 items (10 – 12)	Patil et al. (2024) Harikannan et al. (2025)
	SoP	3 items (13 – 15)	Patil et al. (2024) Harikannan et al. (2025)
	EnP	3 items (16 – 18)	Patil et al. (2024) Harikannan et al. (2025)

1.1.1.1 Data collection techniques:

The study employed a survey questionnaire to collect data from managers of Saudi manufacturing firms, aiming to examine the impact of

Digital Twins' Readiness (DTR) (independent variable) on Sustainable Performance (SP) (dependent variable). The questionnaire consists of two main sections:

1- Demographic composition: This section provides an overview of the respondents' characteristics, incorporating key demographic variables such as age, gender, educational background, professional experience, managerial level, and industry type, to ensure a comprehensive understanding of the sample population.

2- The impact of DTR (x) on SP (y): This section utilizes a series of structured items to explore managers' perceptions of how DTR affects the SP of Saudi manufacturing firms. It aims to assess the extent to which DTR contributes to enhancing sustainability across economic, social, and environmental dimensions.

The instrument utilizes a 5-point Likert scale, ranging from 1 "strongly disagree" to 5 "strongly agree". All items are positively phrased, such that higher scores denote more favorable outcomes, whereas lower scores signify less favorable results.

Research population and sample:

The research population for this study comprises managers of Saudi manufacturing firms. Given the undefined sampling frame and the vast nature of the population, a non-probability Convenience Sampling Technique (CST) was employed, allowing for participant selection based on accessibility and willingness to respond. Data was gathered using an online questionnaire distributed via Google Forms. Of the 213 responses collected, 12 were excluded due to factors such as duplicate entries, resulting in a final sample of 201 valid responses.

Statistical techniques:

The research model is presented in Figure 7. The study employs Partial Least Squares-Structural Equation Modeling (PLS-SEM) for hypothesis testing. PLS-SEM is designed to address complex relationships among constructs. It is composed of two models: a measurement model (Confirmatory Factor Analysis or CFA) and a structural model (Regression analysis). The former is used to evaluate construct validity and reliability as follows:

1- Construct validity: is composed of convergent validity and discriminant validity. The former indicates the extent to which items of a construct are highly correlated, while the latter evaluates whether the items representing each construct are distinct from other items. Convergent validity is evaluated using factor loadings, and Average Variance Extracted (AVE), whereas discriminant validity is evaluated using the Fornell-Larcker criterion, which indicates that the square root of AVE for each construct must exceed the inter-correlation coefficients between the construct and other constructs.

2- Reliability: is assessed using Cronbach's coefficient α and Composite Reliability (CR).

After confirming both construct validity and reliability, the structural model is utilized to test the research hypotheses and determine relationships between the constructs. Model fit is evaluated using indicators such as the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI). Furthermore, the coefficient of determination (R^2) is utilized to assess the explanatory power of individual paths, while the effect size (f^2) measures the magnitude of the influence exerted by the DT dimensions on SP. According to conventional thresholds, f^2 values greater than 0.02, 0.15, and 0.30 correspond to small, medium, and large effects, respectively.

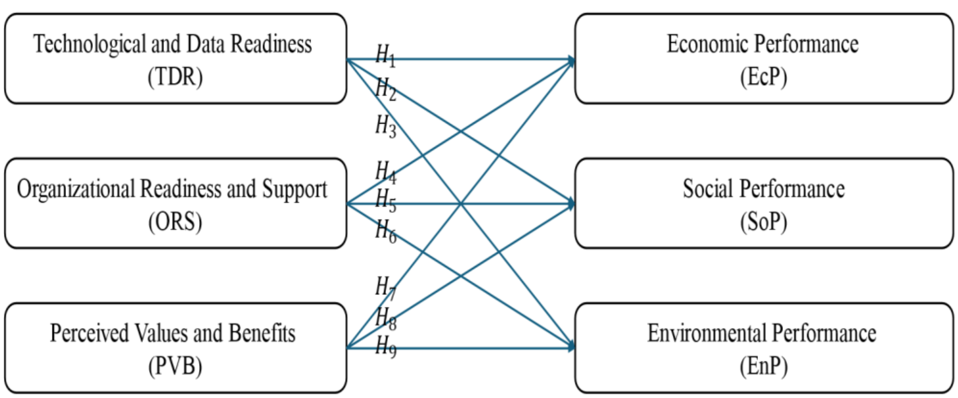

Figure 7 Research model

Findings and data analysis:

This section presents the results of data analysis and hypothesis testing. It is divided into three themes: the demographic composition of respondents, the measurement model, and the structural model.

Demographic profile:

The demographic analysis of the study sample (n = 201) provides insights into key characteristics of managers within Saudi firms. The study utilized frequency tables to summarize sample demographics, including gender, work experience, firm size, and industry sector. The demographic composition is depicted in Table 2.

Table 2 Demographic profile

Demographic Variables	Total	%
***Gender* ($n = 201$)**		
Male	135	67.2%
Female	66	32.8%
***Work Experience* ($n = 201$)**		
Less than 5 years	28	13.9%
5 – 10 years	43	21.4%
11 – 15 years	84	41.8%
More than 15 years	46	22.9%
***Firm size* ($n = 201$)**		
Micro Enterprise (1 – 9	46	22.9%
Employees)	37	18.4%
Small Enterprise (10 – 49	83	41.3%
Employees)	35	17.4%
Medium Enterprise (50 – 249		
Employees)	32	15.9%
Large Enterprises (1000 or more	34	16.9%
Employees)	60	29.9%
***Industry sector* ($n = 201$)**	27	13.4%
Food & Beverages	14	7.0%
Pharmaceuticals	11	5.5%
Automative	11	5.5%
Energy and Utility	12	6.0%
Apparel and Textile		
Consumer Goods		

Consumer Electronics **Others**		

The gender distribution indicates that males dominate the sample, with a percentage of 67.2% (n = 135) of total respondents, while females constitute 32.8% (n = 66). As for work experience, most managers fall within the "11 – 15 years" group, representing 41.8% (n = 84) of the sample. Managers with more than 15 years of experience represent 22.9% (n = 46), with 5 – 10 years of experience 21.4% (n = 43), while those with less than 5 year of experience comprise 13.9% (n = 28). Based on firm size, most respondents work in medium enterprises (50 – 249 employees), accounting for 41.3% (n = 83). Additionally, 22.9% (n = 46) work in micro enterprises (1 – 9 employees), and 18.4% (n = 37) work in small-sized firms (10 – 49 employees), and 17.4% (n = 35) work in large enterprises (1000 employees or more).

The industry distribution illustrates that the largest proportion, 29.9% (n = 60), falls under the "Automative" category. This is followed by the "Pharmaceuticals" industry, which accounts for 16.9% (n = 34) of respondents. The "Food & Beverages" sector represents 15.9% (n = 32), while "Energy and Utility" sector comprises 13.4% (n = 27). The "Apparel and Textile" sector constitutes 7% (n = 14) of respondents. The "Others" category represents 6% (n = 12), indicating that a small proportion of participants are employed in industry sectors not identified in the analysis. The "Consumer Goods" and "Consumer Electronics" sectors each make up 5.5% (n = 11).

The findings indicate that sampled managers within Saudi firms are professionally experienced males. Most managers are employed in medium enterprises comprising 50 to 249 employees. Additionally, a considerable proportion are engaged in the "Automative" sector.

The measurement model:

The convergent validity of constructs measures the extent to which multiple indicators of a given variable are correlated. It is evaluated using average variance extracted (AVE) and factor loadings, both of which should exceed at least 0.5 to ensure adequate validity. As presented in Table 3, the AVE and factor loadings exceed the threshold of 0.7, indicating strong convergent validity. This suggests that the measured indicators effectively capture the underlying construct, ensuring the reliability of the measurement model. Additionally, the researcher evaluates the reliability of the measurement scales using Cronbach's coefficient α and Composite Reliability (CR). A scale is considered reliable if its Cronbach's coefficient α and CR are greater than or equal to 0.7. As demonstrated in Table 3, each scale has Cronbach's coefficient α and a CR that exceeds 0.7, confirming their reliability.

Table 3 Convergent validity and reliability

Construct	**Items**	**Factor Loadings**	**Variance Inflation Factors (VIFs)**	**Cronbach's α**	**Composite Reliability (CR)**	**Average Variance Extracted (AVE)**
		Must > 0.7	Must < 3	Must > 0.7	Must > 0.7	Must > 0.7
Technological and Data Readiness (TDR)	TDR1	0.885	2.087	0.824	0.831	0.740
	TDR2	0.883	2.149			
	TDR3	0.810	1.606			
Organizational Readiness and Support (ORS)	ORS1	0.861	1.857	0.850	0.851	0.770
	ORS2	0.882	2.232			
	ORS3	0.889	2.287			
Perceived Values and Benefits (PVB)	PVB1	0.876	1.958	0.810	0.813	0.725
	PVB2	0.819	1.585			
	PVB3	0.859	1.918			
Economic Performance (EcP)	EcP1	0.837	1.686	0.818	0.821	0.734
	EcP2	0.885	2.054			
	EcP3	0.848	1.845			
Social Performance (SoP)	SoP1	0.844	1.739	0.801	0.802	0.716
	SoP2	0.873	1.937			
	SoP3	0.820	1.595			
Environmental Performance (EnP)	EnP1	0.870	1.981	0.840	0.841	0.757
	EnP2	0.883	2.092			
	EnP3	0.858	1.895			

Discriminant validity is assessed using the Fornell–Larcker criterion, which states that the square root of the AVE for each construct must be greater than its correlation with any other construct. This ensures that each construct is distinct and measures a unique concept within the model. As shown in Table 4, the square root of AVE of each construct exceeds its correlation with other constructs, confirming the discriminant validity of constructs.

Table 4 Discriminant validity using Fornell–Larcker criterion

Variables	TDR	ORS	PVB	EcP	SoP	EnP
TDR	**0.860**					
ORS	0.697	**0.877**				
PVB	0.671	0.727	**85.2**			
EcP	0.767	0.778	0.767	**0.857**		
SoP	0.707	0.713	0.695	0.686	**0.846**	
EnP	0.677	0.675	0.705	0.630	0.616	**0.870**

The structural model and hypothesis testing:

The structural model is illustrated in Figure 8, and its results are summarized in Table 5. Results indicated that TDR positively and significantly affected EcP (β = 0.338, t-value = 5.726, p-value = 0.000), SoP (β = 0.324, t-value = 4.825, p-value = 0.000), and EnP (β = 0.289, t-value = 3.558, p-value = 0.000). Therefore, H_1, H_2, and H_3 are supported.

Similarly, ORS positively and significantly affected EcP (β = 0.318, t-value = 4.822, p-value = 0.000), SoP (β = 0.297, t-value = 2.826, p-value = 0.005), and EnP (β = 0.217, t-value = 2.233, p-value = 0.026). Therefore, H_4, H_5, and H_6 are supported.

Ultimately, PVB positively and significantly affected EcP (β = 0.310, t-value = 4.598, p-value = 0.000), SoP (β = 0.262, t-value = 3.112, p-value = 0.002), and EnP (β = 0.353, t-value = 3.838, p-value = 0.000). Thus, all research hypotheses are supported. Therefore, H_7, H_8, and H_9 are supported.

Table 5 Structural model results

Hypothesis	Relationship	Path coefficient β	t statistic ($\|O/STDEV\|$)	p-value	C.I		Support for Hypothesis
					Min	Max	
H_1	TDR → EcP	0.338	5.726	0.000	0.217	0.449	Yes
H_2	TDR → SoP	0.324	4.825	0.000	0.187	0.450	Yes
H_3	TDR → EnP	0.289	3.558	0.000	0.137	0.453	Yes
H_4	ORS → EcP	0.318	4.822	0.000	0.187	0.445	Yes
H_5	ORS → SoP	0.297	2.826	0.005	0.089	0.501	Yes
H_6	ORS → EnP	0.217	2.233	0.026	0.019	0.399	Yes
H_7	PVB → EcP	0.310	4.598	0.000	0.185	0.449	Yes
H_8	PVB → SoP	0.262	3.112	0.002	0.099	0.428	Yes
H_9	PVB → EnP	0.353	3.838	0.000	0.168	0.526	Yes

Furthermore, as shown in Table 6, the model exerted goodness of fit with a SRMR (0.053) below 0.08, and a NFI (0.830) that exceeds normal average and approaches 0.90. Also, the R^2 of each path (EcP = 0.744, SoP = 0.622, and EnP = 0.591) confirms the model's goodness of fit.

Table 6 Model fit

Construct	R-square (R^2)	Adjusted R-square	SRMR	NFI
EcP	0.744	0.740	0.053	0.830
SoP	0.622	0.617		
EnP	0.591	0.585		

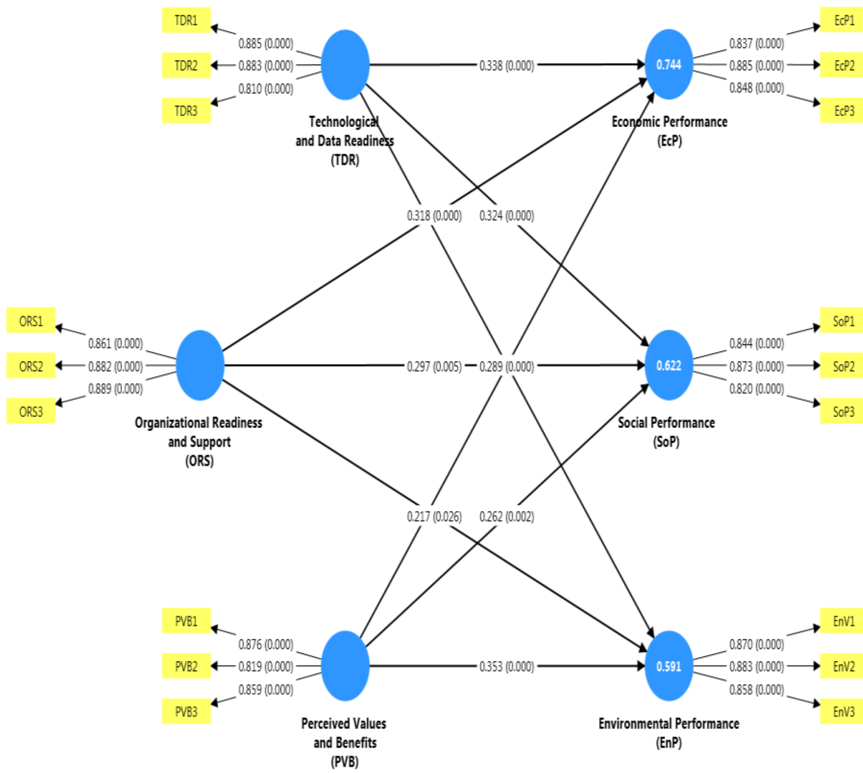

Figure 8 Structural model

The effect size (f^2), which indicates the magnitude of the contribution of DTR to sustainable performance, is presented in Table 7. Results indicate that TDR, ORS, and PVB have a moderate effect on EcP, but a small one on both SoP and EnP.

Table 7 Effect size

Relationship	f^2	Effect size
TDR → EcP	0.204	Moderate
TDR → SoP	0.127	Small
TDR → EnP	0.093	Small
ORS → EcP	0.155	Moderate
ORS → SoP	0.091	Small
ORS → EnP	0.045	Small
PVB → EcP	0.157	Moderate
PVB → SoP	0.076	Small
PVB → EnP	0.128	Small

Discussion:

This study offered valuable insights into the role of Digital Twin Readiness (DTR), encompassing Technological and Data Readiness (TDR), Organizational Readiness and Support (ORS), and Perceived Values and Benefits (PVB), in enhancing Sustainable Performance (SP) within Saudi manufacturing firms. Based on a field study, the research explored the views of managers on how these DTR dimensions contribute to the sustainability outcomes of manufacturing operations in Saudi Arabia.

The findings highlight Technological and Data Readiness (TDR) as a key driver in improving the sustainable performance of manufacturing firms (SP). This underscores the importance of a solid technological infrastructure and capability in adopting and leveraging Digital Twin (DT) technologies to drive improvements across environmental, economic, and social sustainability dimensions. This finding aligns with existing literature that emphasizes the role of technological and data readiness in enabling the effective deployment of DT, which in turn enhances sustainable manufacturing practices and overall sustainable performance. It also help explain Saudi Arabia’s strategic investments in strengthening the technological and data infrastructure of its industrial sector to support digital innovation and sustainability goals. A high level of data quality, accessibility, and integration supports the effective deployment of DTs, enabling organizations to monitor processes in real time, make data-informed decisions, and optimize resource use, all of which are critical to achieving sustainability targets.

In line with the literature, the study indicates that Organizational Readiness and Support (ORS) has a significant positive impact on the sustainable performance of manufacturing firms (SP). This finding emphasizes that strong leadership, dedicated organizational support, and proper allocation of resources are crucial for building a culture that embraces Digital Twin technologies and drives their successful integration to support sustainable outcomes. It also illustrates the drive among Saudi manufacturing firms to integrate digital technologies, such as Digital Twins, as a strategic approach to achieving their sustainability goals.

The study further shows that Perceived Values and Benefits (PVB) positively and significantly influence sustainable performance (SP). When managers recognize the tangible and intangible benefits of DT, such as enhanced efficiency, innovation, and reduced operational costs, they are more likely to support and engage with its adoption, reinforcing sustainable initiatives. This finding aligns with previous studies, emphasizing the potential benefits of DTR for enhancing the sustainable performance of Saudi manufacturing firms. It also indicates that Saudi managers possess sufficient IT skills and awareness, which helps to reduce resistance to technology adoption and facilitates smoother implementation of digital solutions.

Conclusions:

The study concluded that firms demonstrating strong readiness to implement Digital Twin (DT) technologies tend to perform better in terms of sustainability. This has prompted Saudi manufacturing companies to prioritize investments in digital infrastructure and workforce development. By equipping employees with relevant digital skills and fostering an environment conducive to technological adoption, these firms are better positioned to leverage DT solutions. Ultimately, this facilitates improved operational efficiency, reduced environmental impact, and stronger alignment with long-term sustainability goals.

The practical implications of these findings are substantial. They suggest that Saudi manufacturing firms should prioritize enhancing their digital infrastructure and investing in workforce training to ensure successful DT adoption. Managers are encouraged to foster a culture of innovation and technological openness, ensuring organizational readiness and support at all levels. Additionally, aligning technological initiatives with sustainability goals can create long-term value, not only by improving operational efficiency but also by strengthening environmental and social performance.

While this study provides important insights, several limitations should be acknowledged. Firstly, the data was drawn from a sample of 201 managers in Saudi manufacturing firms, which may limit the broader applicability of the results to other regions or industries. Secondly, the study focused on only three dimensions of Digital Twin Readiness (DTR), which are Technological and

Data Readiness (TDR), Organizational Readiness and Support (ORS), and Perceived Values and Benefits (PVB), while existing literature suggests that there are additional dimensions worth examining. Future research should investigate how other Industry 4.0 technologies, such as Artificial Intelligence (AI), Internet of Things (IoT), and blockchain, affect sustainable performance in manufacturing and beyond. It is also recommended that sustainable performance be disaggregated into its core dimensions (economic, environmental, and social) to better understand how each is influenced by digital technologies like DT. Further studies could explore the differential impact of DTR across industries, firm sizes, and geographic locations to provide nuanced insights. Cross-country comparisons may also reveal how cultural norms, regulatory frameworks, and infrastructure maturity influence the success and sustainability outcomes of DT adoption.

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