

**IMPACT OF DIGITAL TWIN IMPLEMENTATION
ON THE CONSTRUCTION PROJECTS SUCCESS IN
SAUDI ARABIA**

BY

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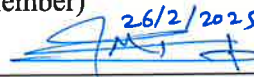
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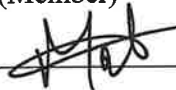
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DEDICATION

I Solely Dedicate my Thesis to My Beloved Family and Friends

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I would like to express my heartfelt gratitude to my dedicated supervisor, Dr. Awsan Mohammed, for your unwavering guidance, mentorship, and invaluable support throughout the research process. Your expertise and encouragement have been instrumental in shaping this work.

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ABSTRACT

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With growing complexity in construction projects, there is a need for tools that enhance efficiency, decision-making, and stakeholder communication. Digital Twins virtual models that represent, simulate, and predict real-time project conditions offer significant potential in this regard. However, there has been limited research on how different aspects of Digital Twins contribute to project success. This research investigates the impact of Digital Twin technology on construction project success, focusing on how it influences Project Management and Leadership, Project Efficiency, Stakeholder Satisfaction, and Business Success.

This study tested 16 hypotheses across four Digital Twin features: Representation and Modelling, Data Handling and Integration, Communication and Interaction, and Functional Capabilities and Security. Partial Least Squares Structural Equation Modelling (PLS-SEM) is used for the analysis. Data were collected from industry professionals, allowing an in-depth analysis of these factors' effects on project outcomes. The framework was validated through qualitative insights gathered from two case studies, highlighting the interdependencies and collective impact of Digital Twin characteristics on project success. This process demonstrated how the framework effectively captures the relationships between Digital Twin features and critical success factors, emphasizing their influence on project management, efficiency, stakeholder satisfaction, and overall business success.

The results revealed that three key features of Digital Twins Representation and Modeling, Data Handling and Integration, and Functional Capabilities and Security demonstrated significant positive impacts on project outcomes. For instance, Representation and Modeling had a strong influence on Project Management and Leadership ($p = 0.000$) and Project Efficiency ($p = 0.000$), emphasizing its critical role in enabling proactive planning and risk management. Similarly, Data Handling and Integration contributed significantly to Stakeholder Satisfaction ($p = 0.004$) and Business Success ($p = 0.036$), highlighting the importance of real-time data integration for effective decision-making. These findings provide empirical evidence of the specific functionalities that drive project success and offer a targeted framework for optimizing Digital Twin adoption in construction projects.

The practical implications of this study highlight the need for construction firms to prioritize Representation and Modeling, Data Handling and Integration, and Functional Capabilities and Security when implementing Digital Twins. These features enable real-time data insights, predictive analytics, and seamless system integration, which drive better decision-making, resource optimization, and stakeholder engagement. By adopting these functionalities, organizations can enhance project efficiency, reduce risks, and improve overall project outcomes. This research provides a clear framework for leveraging Digital Twin technology to address the complexities of modern construction projects and achieve sustainable success.

ملخص الرسالة

الاسم الكامل: حسن عبد الكريم حسن عبد القادر

عنوان الرسالة: أثر تطبيق التوائم الرقمي على نجاح مشاريع البناء في المملكة العربية السعودية

التخصص: إدارة وهندسة التشييد

تاريخ الدرجة العلمية: 2024/12/11

مع تعقيد المشاريع الإنشائية المتزايد، تظهر الحاجة إلى أدوات تعزز الكفاءة واتخاذ القرارات والتواصل بين أصحاب المصلحة. توفر التوائم الرقمية، كنماذج افتراضية تمثل وتحاكي وتوقع ظروف المشاريع في الوقت الفعلي، إمكانات كبيرة في هذا المجال. ومع ذلك، هناك نقص في الأبحاث حول كيفية مساهمة جوانب التوائم الرقمية المختلفة في نجاح المشاريع. يبحث هذا البحث في تأثير تقنية التوائم الرقمي على نجاح المشاريع الإنشائية، مع التركيز على تأثيرها على إدارة المشروع والقيادة، كفاءة المشروع، رضا أصحاب المصلحة، ونجاح الأعمال. باستخدام نمذجة المعادلات الهيكلية بالحد الأدنى للمربعات الجزئية (PLS-SEM)، تم اختبار 16 فرضية عبر أربعة ميزات للتوائم الرقمية: التمثيل والنمذجة، معالجة البيانات والتكامل، التواصل والتفاعل، والقدرات الوظيفية والأمان.

تم جمع البيانات من محترفين في الصناعة، مما أتاح تحليلاً عميقاً لتأثير هذه العوامل على نتائج المشاريع. وتم التحقق من الإطار من خلال رؤية نوعية تم جمعها من دراسية حالة، لتوضيح العلاقات المتبادلة والتأثير المشترك لخصائص التوائم الرقمية على نجاح المشاريع. أثبتت هذه العملية فعالية الإطار في التقاط العلاقات بين ميزات التوائم الرقمية وعوامل النجاح الحرجة، مع التركيز على تأثيرها على إدارة المشاريع والكفاءة ورضا أصحاب المصلحة ونجاح الأعمال ككل.

كشفت النتائج أن ثلاث ميزات رئيسية للتوائم الرقمية، وهي التمثيل والنمذجة، ومعالجة البيانات والتكامل، والقدرات الوظيفية والأمان، لها تأثيرات إيجابية كبيرة على نتائج المشاريع. على سبيل المثال، كان للتمثيل والنمذجة تأثير قوي على إدارة المشروع والقيادة ($p = 0.000$) وكفاءة المشروع ($p = 0.000$)، مما يبرز دوره الحاسم في تعزيز التخطيط الاستباقي وإدارة المخاطر. وبالمثل، ساهمت معالجة البيانات والتكامل بشكل كبير في رضا أصحاب المصلحة ($p = 0.004$) ونجاح الأعمال ($p = 0.036$)، مما يبرز أهمية دمج البيانات في الوقت الفعلي لاتخاذ قرارات فعالة. في المقابل، لم يظهر التواصل والتفاعل تأثيرات

كبيرة عبر المتغيرات التابعة، حيث كانت النتائج مثل ($p = 0.750$) لكفاءة المشروع، مما يشير إلى أن الشفافية المستندة إلى البيانات قد تقلل من الاعتماد على طرق التواصل التقليدية.

توفر هذه النتائج دليلاً تجريبياً على الوظائف المحددة التي تدفع نجاح المشاريع وتقدم إطاراً مستهدفاً لتحسين تبني التوائم الرقمية في المشاريع الإنشائية.

على الصعيد العملي، تبرز الآثار العملية لهذه الدراسة الحاجة إلى أن تعطي الشركات الإنشائية الأولوية لميزات التمثيل والنمذجة، ومعالجة البيانات والتكامل، والقدرات الوظيفية والأمان عند تنفيذ التوائم الرقمية. هذه الميزات تُمكن من الوصول إلى رؤى بيانات في الوقت الفعلي، وتحليلات تنبؤية، وتكامل سلس للأنظمة، مما يعزز اتخاذ القرارات، وتحسين الموارد، وتعزيز مشاركة أصحاب المصلحة. من خلال اعتماد هذه الوظائف، يمكن للمنظمات تعزيز كفاءة المشاريع وتقليل المخاطر وتحسين النتائج العامة للمشاريع. يقدم هذا البحث إطاراً واضحاً للاستفادة من تقنية التوأم الرقمي لمواجهة تعقيدات المشاريع الإنشائية الحديثة وتحقيق النجاح المستدام.

CHAPTER 1

INTRODUCTION

1.1 Overview

The concept of digital twins has been evolving for decades, with its origins tracing back to early simulation models and virtual prototypes, gaining significant traction with advancements in computing, data analytics, and sensor technologies, but its broader adoption only became practical with advancements in sensors, analytics, and machine learning technologies. One of the earliest examples of digital twin-like models dates back to the 1960s, when NASA employed "mirror models" to simulate space missions and test spacecraft designs virtually before construction [1].

In the 1990s, the concept gained traction in manufacturing, and in 2002, Michael Grieves formally introduced the term "digital twin." He described it as a virtual representation of physical products or processes, emphasizing its ability to bridge the physical and digital domains. During this period, the development of the Internet of Things (IoT) and increased availability of sensors and data sources further strengthened the feasibility of digital twins. By combining real-time sensor data with machine learning and advanced analytics, highly detailed digital models of physical systems became achievable [1]. The manufacturing industry has been at the forefront of adopting digital twins, leveraging them for process optimization, reducing downtime, and improving both quality and efficiency, making it one of the most successful applications of this technology [2].

In recent years, digital twins have expanded into other sectors, such as transportation, healthcare, and construction. For instance, in transportation, digital twins enhance vehicle performance and optimize traffic systems. In healthcare, they simulate surgical procedures and improve treatment strategies, leading to better patient outcomes. Digital twins have also revolutionized smart city development, facilitating the planning and management of urban infrastructure. By creating virtual replicas of cities, stakeholders can simulate and optimize traffic, energy usage, waste management, and emergency responses, contributing to more sustainable and efficient urban environments [28]. The integration of machine learning and artificial intelligence (AI) has further propelled digital twin advancements. These technologies process vast amounts of data, uncover patterns, and extract insights that would be challenging for humans to identify. This has enabled the development of predictive digital twins, capable of simulating complex scenarios with remarkable accuracy [2]. Through these advancements, digital twins have established themselves as a transformative tool across industries, driving efficiency and innovation while addressing challenges in diverse applications

1.2 Theoretical Foundations of Digital Twins

The historical evolution of digital twin (DT) technology highlights its varied definitions and applications. Several key terms related to DT have been clarified to provide a comprehensive understanding of the concept. Grieves and Vickers [2] defined a digital twin as “a set of virtual information constructs that comprehensively describe a physical product, from micro atomic details to macro geometrical characteristics, enabling any information obtainable from the physical product to be accessed from its digital counterpart.”

The Digital Twin Prototype (DTP) represents the initial virtual model of a physical artifact. This prototype includes all critical information needed to produce a corresponding physical version, ensuring the virtual and physical models are aligned. Parris [5] expanded on this by introducing the concept of the Digital Twin Instance (DTI), which refers to the digital counterpart of a specific physical product, remaining linked throughout the product's lifecycle. The DTI encompasses detailed data, including annotated 3D models with Geometric Dimensioning and Tolerancing (GD&T), bills of materials and processes, service records, and real-time operational data gathered via sensors [4]. Furthermore, Grieves and Vickers [2] introduced the Digital Twin Aggregate (DTA), which represents the aggregation of all DTIs within a system. The DTA acts as a computational construct capable of querying individual DTIs either proactively or on demand, although it does not exist as a standalone data structure. Another key concept is the Digital Twin Environment (DTE), which integrates multi-domain physics applications to operate on digital twins for predictive analysis and problem-solving purposes. The DTE is essential for managing DTPs, DTIs, and DTAs throughout a product's lifecycle.

The application of digital twins spans the entire product lifecycle, beginning with the design phase. A DTP is used to predict performance, validate designs, and ensure quality before physical production begins. Advances in CAD software enable the development of detailed 3D models that can simulate various scenarios and facilitate stakeholder collaboration [6]. This process is classified into three stages: conceptual design, detailed design, and virtual verification, allowing for rigorous testing using environmental, material, and customer data, as well as historical insights from previous generations. Siemens [7] emphasizes the role of DTP in improving product design efficiency, referring to it as the Product Digital Twin, which allows virtual validation of product performance to meet specifications. Figure 1

illustrates this process in detail. These advancements showcase the transformative potential of digital twins in improving product development, optimizing performance, and ensuring operational excellence across industries.

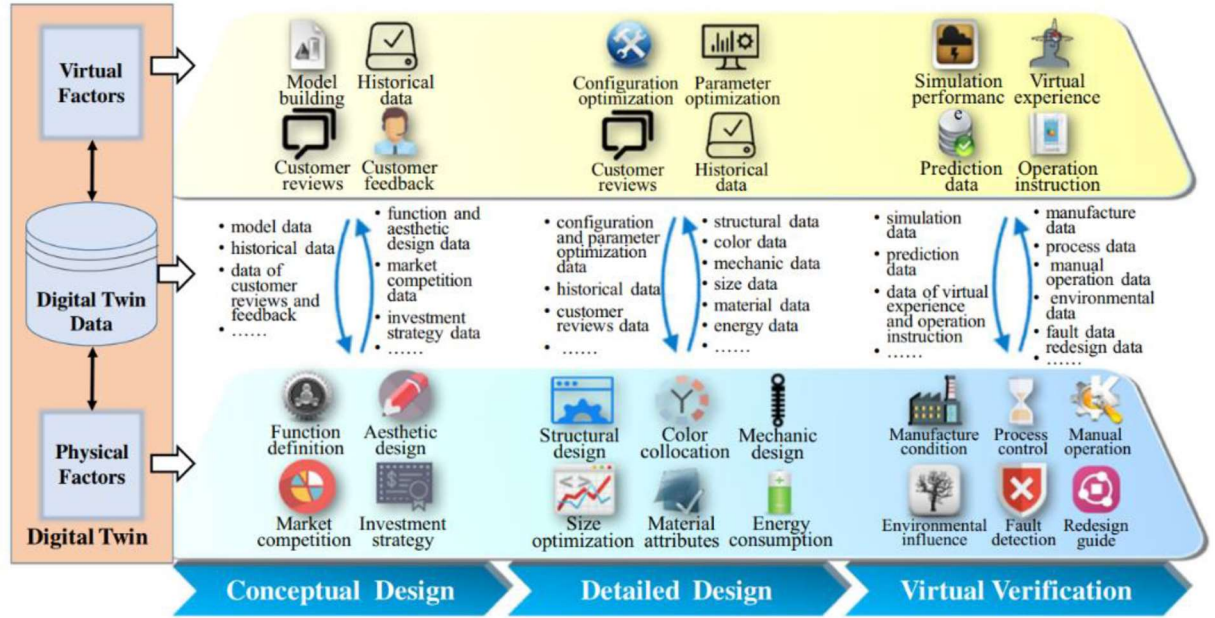


Figure 1: *Digital Twin has Enabled Design process into manufacturing. Source: [6]*

Tao [6] highlighted that the digital twin (DT) concept can be effectively applied during the manufacturing phase to optimize resource allocation, enhance production planning, and improve process control. They introduced the Digital Twin Shop Floor (DTSF), an iterative optimization framework that integrates physical and information spaces. The DTSF framework consists of four primary components: the Physical Shop Floor (PS), the Virtual Shop Floor (VS), the Shop Floor Service System (SSS), and the Shop Floor Digital Twin Data (SDTD). By connecting data from the Digital Product Twin (DTP) with the DTSF, manufacturers can simulate production processes, predict equipment failures, and schedule preventive maintenance. This real-time synchronization results in more efficient, reliable, and cost-effective manufacturing operations. Similarly, Siemens [7] explored the potential

of the Digital Production Twin, emphasizing its role in simulating production processes to develop methodologies that enhance overall productivity.

Digital twin technology also extends its applications to the operational or service phase of the product lifecycle, a stage often characterized by complex structures and layered data. Defects at this stage can result in malfunctions or safety risks, necessitating proactive maintenance strategies. Tao [6] proposed a framework leveraging real-time monitoring with advanced sensors and communication systems to collect critical data, including energy consumption, user operations, product performance, material structure, and component wear. By integrating real-time and historical data, manufacturers gain valuable insights into the operational state of products, enabling services such as energy consumption analysis, user behaviour analysis, and failure prediction. Siemens [7] also introduced the Performance Digital Twin, designed to capture data from operational products, enabling informed decision-making and enhancing both product and system efficiency. This approach transitions manufacturers from reactive maintenance practices, based on heuristics and worst-case scenarios, to a proactive strategy driven by real-time data and advanced analytics. Figure 2 provides a concise overview of these frameworks, including the Performance Digital Twin by Siemens.

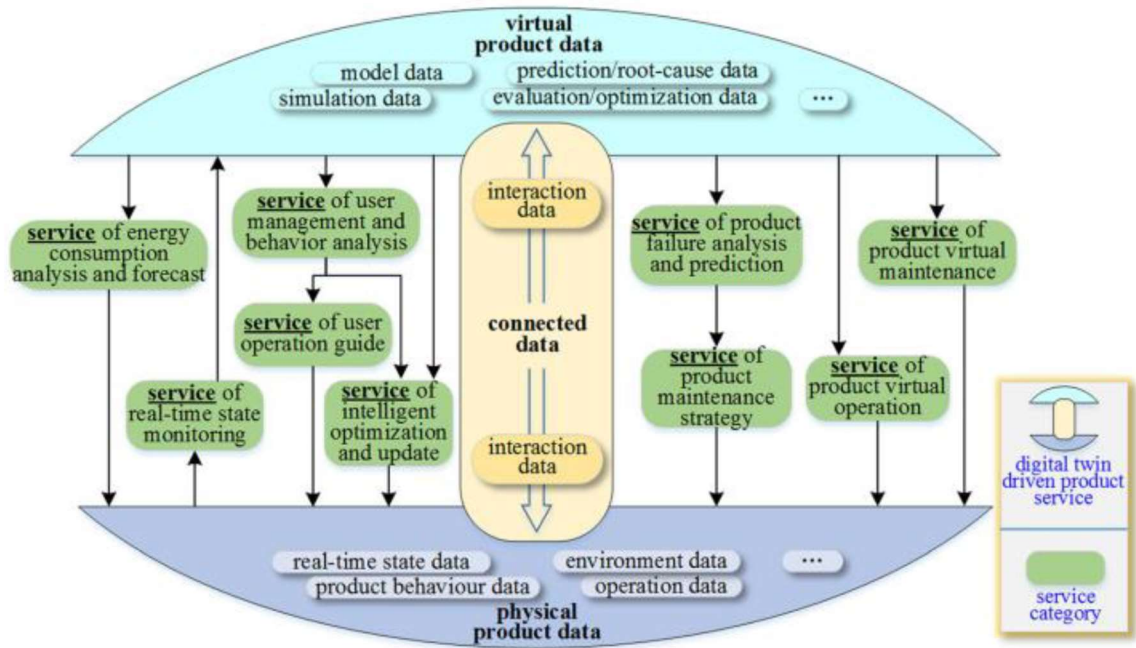


Figure 2: Digital twin concept for monitoring operational phase described by [6]

1.3 Digital Twin in Construction

Digital Twin technology is revolutionizing the construction industry by offering a virtual counterpart that mirrors physical assets and their processes throughout the project lifecycle. This innovative approach integrates advanced digital modeling with real-time data, enabling improved planning, monitoring, and decision-making. By bridging the gap between the physical and digital realms, Digital Twins provide construction stakeholders with actionable insights, enhancing efficiency, sustainability, and project outcomes. This section delves into the foundational theory of Digital Twins in construction, with a focus on their representation and transformative applications.

1.3.1 Theory of Digital Twins in Construction

The integration of digital twins in the construction industry marks a significant technological advancement, transforming how projects are designed, executed, and maintained. This

concept involves the development and synchronization of a virtual counterpart (the digital twin) that replicates the physical structure or infrastructure and its associated processes. By enabling real-time data exchange and advanced simulations, digital twins provide a dynamic and comprehensive view of construction assets throughout their lifecycle. This innovative approach enhances decision-making, efficiency, and sustainability in construction, laying the foundation for smarter and more adaptive building practices [8].

1. Digital Twin Representation: At the core of the digital twin theory is the creation of a comprehensive and accurate virtual representation of a physical asset. This digital twin is a high-fidelity 3D model that encapsulates not only the structural and architectural aspects but also incorporates data related to materials, systems, and operations. This representation serves as a dynamic, data-rich mirror of the physical asset throughout its entire lifecycle [8].

2. Lifecycle Integration: Digital twins extend beyond the construction phase to encompass the entire lifecycle of an asset. This includes design, construction, operations, maintenance, and even decommissioning. The theory posits that by continuously updating and integrating data throughout this lifecycle, stakeholders can make informed decisions, optimize performance, and ensure long-term sustainability [9].

3. Real-Time Data Integration: A critical aspect of digital twins is the integration of real-time data from various sources, including sensors, IoT devices, and building management systems. This real-time data feeds into the digital twin, enabling stakeholders to monitor and manage the asset's performance, energy consumption, and overall health [10].

4. Interdisciplinary Collaboration: Successful implementation of digital twins in construction requires close collaboration among various stakeholders, including architects, engineers, contractors, facility managers, and data analysts. The theory emphasizes the

importance of interdisciplinary teams working together to develop, update, and utilize the digital twin effectively.

5. Decision Support and Predictive Analytics: Digital twins offer robust decision support capabilities through data analytics and simulations. This theory asserts that by leveraging historical data and predictive modeling, stakeholders can anticipate maintenance needs, optimize energy consumption, and make informed decisions to improve asset performance [11].

6. Visualization and Communication: Effective visualization tools are integral to the digital twin theory. The digital twin serves as a visual medium for communicating complex information to stakeholders in a comprehensible manner. This aids in problem solving, collaboration, and decision-making throughout the asset's lifecycle [12].

7. Sustainability and Resilience: Digital twins contribute to sustainability by enabling stakeholders to monitor and optimize resource consumption, reduce waste, and minimize environmental impacts. Furthermore, the theory suggests that digital twins can enhance the resilience of assets by facilitating rapid response to unforeseen events or disasters [13].

The construction industry plays a crucial role in shaping the built environment, but it is also known for its complexities and inherent challenges. Ensuring efficient project execution, minimizing risks, and ensuring the safety of workers are constant concerns. In recent years, the emergence of digital twin technology has offered new possibilities for addressing these challenges in the construction industry. Digital twins have gained significant attention as a transformative technology that can revolutionize the way construction projects are planned, executed, and managed [14].

A digital twin can be defined as a virtual replica or digital representation of a physical object, system, or process. It incorporates real-time data and simulation capabilities to create a dynamic and interactive digital model. Digital twins have been successfully applied in various industries, such as manufacturing and aerospace, to optimize operations, improve decision-making, and enhance overall performance. In the context of construction, digital twins hold immense potential for improving project outcomes and ensuring the safety of workers. By creating a virtual replica of a construction site, digital twins enable real-time monitoring, analysis, and prediction of various parameters, including worker activities, equipment utilization, and environmental conditions. This provides construction professionals with unprecedented insights and the ability to identify potential safety hazards, optimize workflows, and proactively mitigate risks. Furthermore, digital twins facilitate enhanced collaboration and communication among project stakeholders. They provide a shared platform for information exchange, allowing stakeholders to visualize the construction site, simulate safety procedures, and improve coordination. This promotes a proactive and collaborative approach to safety management, ultimately leading to a safer working environment for construction workers.

Despite the immense potential of digital twins in construction, their application for workforce safety is still in its early stages. There is a need for further research and exploration to fully understand the capabilities, limitations, and implementation challenges of digital twins in enhancing safety management practices in construction projects.

1.4 Construction project progress monitoring

According to PMBOK [70], controlling and monitoring a construction project involves processes that are necessary to monitor, review, and manage the project's progress and

performance. These processes help to identify areas where changes may be needed and initiate the corresponding modifications. Project progress is evaluated through inspections and compared to the construction project plans to validate the predicted performance. However, progress monitoring is a challenging task due to the interdependency and complexity of activities, and it is considered a critical success factor for construction projects. It is crucial to have timely and accurate information about a construction project's progress in order to ensure efficient and effective project monitoring that meets the time, cost, quality, and safety requirements. This requires effective on-site data collection, timely data analysis, and clear communication of results to all stakeholders [16]. Regular and systematic monitoring helps project managers and stakeholders identify problems early, prevent delays, and make timely decisions to address any issues, which can prevent unexpected costs resulting from reworks, delays, disputes, and claims. In contrast, poor quality monitoring and management can lead to decreased profitability, delays, cost overruns, and decreased productivity [16]. Monitoring and control of project progress are ongoing and critical tasks in the construction process, involving the periodic measurement of actual progress against the planned or expected progress, monitoring involves checking the actual progress and resource usage against the original plan to make decisions and ensure the project operates as planned.

1.4.1 As-built and As-planned progress data

The term as built refers to the current state of a completed facility or a specific section of a structure following the conclusion of a construction project. In the Architecture, Engineering, and Construction (AEC) industry, as-built data documents the construction process as it actually occurred on-site. This data can be gathered through various approaches.

Traditional progress tracking systems for collecting as-built data faced significant challenges. These systems often relied on manual tools and visual inspections to generate daily, weekly, or monthly reports. While functional, these methods were labor-intensive, prone to errors, and frequently resulted in incomplete or low-quality data. Additionally, the process was time-consuming and costly, limiting its overall effectiveness for construction progress monitoring.

1.4.2 Challenges with construction progress monitoring

Monitoring construction progress is a fundamental aspect of project management, but traditional methods pose significant challenges. Conventional progress tracking systems are labor-intensive, requiring extensive effort to collect and analyze data. Many construction projects lack systematic monitoring frameworks, leaving no clear guidelines for determining when or how to assess progress. Traditional methods rely on manual data collection from various sources, such as schedules, drawings, field reports, and budget documents provided by project managers, foremen, or subcontractors [14],15]. Field personnel typically gather progress data periodically, presenting it in formats like spreadsheets, bar charts, as-built data, or CPM (Critical Path Method) reports. These outputs may also include photographs, videos, or daily and weekly updates. However, such reports are often fragmented and fail to provide timely insights into potential project issues. As a result, project managers must spend significant time organizing and interpreting this information, which delays decision-making. Figure 5 illustrates a typical progress reporting mechanism discussed during coordination meetings, highlighting the limitations of traditional approaches in delivering real-time insights or proactively addressing problems [16].

Manual data collection methods often yield inconsistent results, as the accuracy of progress data depends on the field staff's observations and interpretations. Field workers may have varied perceptions of what should be measured, how measurements should be taken, and how results should be documented. Consequently, the data may not fully represent the impact of site conditions on the project, leading to inaccuracies and potential errors in progress reports.

Additionally, current monitoring practices rely heavily on subjective metrics, making it difficult to obtain precise performance data. For instance, if a subcontractor reports 60% completion of roof work, it remains unclear whether this figure represents the poured concrete volume, the planned material usage, or labor effort. Such ambiguities, coupled with an assumed proportional relationship between inputs and outputs, often result in misleading conclusions. Without thoroughly analyzing construction plans, costs, and resources, progress reports risk inaccuracies, leading to overpayment, overlooked delays, or mismanagement. Reporting methods like progress S curves, bar charts, and textual reports further complicate progress assessments during coordination meetings. These methods fail to intuitively represent multivariable information, such as schedule, cost, and performance, and lack spatial context. As a result, meetings are often consumed by explaining current issues rather than exploring alternative solutions or planning actions to resolve them. This inefficiency hinders participants' ability to quickly and clearly understand the project's status. Furthermore, current monitoring practices prioritize tracking schedules and costs while neglecting quality assessments. The absence of quality metrics in progress reports can lead to rework, rescheduling, and reduced project performance, further emphasizing the need for improved monitoring systems.

In conclusion, integrating digital twin technology into construction processes offers a transformative solution to these challenges. By introducing dynamic, data-driven monitoring, digital twins enable real-time insights, enhance decision-making, and promote efficiency and sustainability throughout the project lifecycle. As technology evolves, adopting digital twins will become increasingly critical to modernizing construction practices.

1.5 Problem statement

In Saudi Arabia, the construction industry is a cornerstone of economic growth and development, pivotal to the nation's ambitious Vision 2030 goals [139]. However, the path to achieve consistent success in construction projects is fraught with challenges. In the pre-construction phase, difficulties arise in realistic planning, design alignment with regulations, and securing funding. During construction, the industry grapples with resource allocation, project management complexities, regulatory compliance, and maintaining health and safety standards. Post-construction challenges include ensuring quality control, managing the handover process, and addressing post-completion defects. Across all phases, managing diverse stakeholder interests, integrating advanced technologies like digital twins, and embedding sustainable practices pose additional hurdles. Despite significant investments and advancements, the industry faces a gap in understanding and addressing the intricate factors that influence project success in the Saudi Arabian context. These factors encompass socio-cultural, regulatory, and environmental dimensions that are critical yet under-explored in influencing the success rates of construction projects.

In response to these challenges, this research focuses on the transformative potential of digital twin technology in revolutionizing project management and execution within the

Saudi Arabian construction sector. Digital twin technology creates a dynamic virtual representation of physical assets, has the potential to significantly impact project planning, execution, and monitoring. However, its integration and impact in the specific context of Saudi Arabia's construction industry have not been extensively studied.

The study will explore the nuances of how digital twin technology interacts with factors affecting construction projects. This includes examining the implications of regulatory frameworks, stakeholder engagement, technology adoption, workforce dynamics, and cultural factors in the context of digital twin implementation. The goal is to provide in-depth insights into customizing project management practices to the unique requirements of Saudi Arabia's construction industry.

1.6 Research Objectives

The main objectives of this research are to:

1. Identify the digital twins' characteristics in the construction industry, which involves a comprehensive research and analysis process to understand how digital twin technology impacts in construction projects.
2. Develop a framework to investigate the impact of digital twin technology adoption and implementation on the construction project's success. The development process combines insights from literature reviews, industry practices, and stakeholder feedback to ensure the framework is both comprehensive and practical. This framework serves as a tool to assess how Digital Twin technology facilitates decision-making, improves operational efficiency, and aligns projects with business goals. So, creating a structured approach makes it possible to evaluate Digital Twin adoption in diverse project contexts.

3. Validate the proposed framework based on a real case study to explore the effectiveness and applicability of the developed framework. This objective involves applying the framework to real-world construction projects in Saudi Arabia and analyzing how Digital Twin functionalities align with and impact project outcomes. Conducting case studies, to identify the successes associated with implementing Digital Twins offering practical insights into its scalability and utility.

1.7 Importance of the Research

The integration of Digital Twin technology into the construction industry marks a transformative shift in how construction projects are managed, executed, and maintained. Digital Twins, serving as virtual representations of physical assets and processes, provide a new dimension to construction management by enabling dynamic, real-time simulations of project elements. These capabilities enhance the ability of stakeholders to visualize complex construction scenarios in a detailed and interactive manner, fostering better communication among project teams, clients, and other involved parties. This improved visualization helps reduce misunderstandings and miscommunications, leading to more informed decision-making and a clearer understanding of project scope and progress [140].

The predictive capabilities of Digital Twins play a crucial role in construction by allowing real-time simulations of various project scenarios. This enables the identification of potential risks and issues early in the project lifecycle. By recognizing these risks ahead of time, project teams can take proactive measures to prevent delays, manage costs, and address unforeseen challenges before they escalate [140]. Predictive analytics within Digital Twins thus not only contribute to more efficient planning but also ensure that resources are allocated effectively, reducing waste and improving overall project reliability.

Digital Twins also provide a robust platform for optimizing project planning. Through their virtual simulation capabilities, project managers can experiment with different strategies, such as sequencing, resource allocation, and scheduling. This allows for more precise planning, as teams can evaluate various scenarios without the risks or costs associated with real-world experimentation. Consequently, project schedules are optimized, and resource utilization is maximized, leading to more efficient project execution [141].

Moreover, Digital Twins enable real-time monitoring and control of construction projects. By integrating data from various sensors and systems, Digital Twins allow construction progress and conditions to be tracked continuously. This is especially beneficial for large-scale projects where multiple stakeholders and complex logistics are involved. With real-time tracking, project managers can identify deviations from the plan and make adjustments promptly, preventing delays and ensuring that projects remain on schedule [141].

Beyond improving communication and coordination during construction, Digital Twins also facilitate collaboration among various project participants. Architects, engineers, contractors, and subcontractors can work more efficiently by sharing a common digital platform where all project data is centralized. This eliminates silos, ensuring that all stakeholders are working with the same information, which enhances coordination and streamlines project execution. As a result, the construction process becomes more cohesive and collaborative, leading to smoother project delivery [140]. After the construction phase, Digital Twins continue to provide value through ongoing performance monitoring and maintenance. They allow for continuous tracking of an asset's health and functionality over time, supporting predictive maintenance and ensuring that assets are properly managed throughout their lifecycle. This is particularly advantageous for facilities management, as it

helps identify issues before they result in costly repairs or operational inefficiencies, ultimately contributing to the long-term sustainability of the built asset [140].

The adoption of Digital Twin technology in construction is not just a technological advancement; it is a key enabler of better project management, risk mitigation, and overall operational efficiency. As the construction industry continues to evolve, Digital Twins represent a critical tool for enhancing collaboration, improving decision-making, and ensuring project success from planning through to maintenance and beyond.

1.8 Limitations of this Research

This study has several limitations, particularly in relation to the data collection process and the evolving nature of Digital Twin adoption in Saudi Arabia. One of the primary limitations is the challenge of obtaining a comprehensive range of stakeholder perspectives involved in the implementation of Digital Twin technology. Despite efforts to engage key stakeholders, including policymakers, developers, contractors, and end-users, there are inherent constraints such as accessibility, willingness to participate, and representation. These factors may limit the diversity and breadth of viewpoints captured, potentially impacting the depth and generalizability of the findings. For instance, certain stakeholders may be underrepresented due to their limited involvement or understanding of Digital Twin applications, which could affect the overall perspectives on its effectiveness and future potential.

Additionally, the relatively nascent stage of Digital Twin adoption in Saudi Arabia introduces another limitation. While there is significant interest in the technology, the implementation and integration of Digital Twin systems are still in their early stages within the construction industry. This means that data on the practical applications and impacts of

Digital Twins may be limited or insufficient, especially in the context of real-world case studies. The lack of established best practices and benchmarks within the country further complicates the ability to draw definitive conclusions regarding the widespread use and effectiveness of Digital Twins in construction projects. As the technology continues to evolve, ongoing research will be required to capture the full scope of its potential and challenges, as well as to assess its long-term impacts on project outcomes. Furthermore, the data collection process itself poses challenges in a rapidly developing field like Digital Twin technology. The availability of accurate, up-to-date data on Digital Twin implementation is limited, and the speed at which technology is being adopted means that there is often a gap between theoretical advancements and practical, on-the-ground implementation. As a result, the findings of this study may not fully reflect the future trajectory of Digital Twin adoption in Saudi Arabia, as the landscape is likely to change significantly over time. Additionally, the complexity and scale of construction projects using Digital Twins make it difficult to assess every variable that could influence project success, further limiting the scope of this research.

Lastly, the sample size of stakeholders and projects used for the study may also limit the generalizability of the results. Given the limited number of projects that have fully adopted Digital Twin technology in Saudi Arabia, the research is based on a relatively small dataset. This may limit the ability to make broad conclusions about the overall impact of Digital Twins on the construction industry, especially in terms of long-term economic, social, and environmental outcomes. These limitations emphasize the need for continued research as Digital Twin technology matures within the construction industry in Saudi Arabia. As the technology becomes more widespread and the data on its application expands, future studies

will be better positioned to provide comprehensive insights into its long-term effects and potential for revolutionizing construction practices.

1.9 The organization of the research

Chapter 1 Introduction: In this chapter, which serves as an introduction to the thesis, the main themes of the study are outlined, the background of the research is presented, and the research problem that the study aims to tackle is clearly defined. The chapter shed light on the existing gap in research and put forth relevant research questions, objectives, and the aim of the study. Following that, it provided an overview of the contextual and geographic boundaries, summarized the chosen research methodology, and emphasized the significance and importance of the study.

Chapter 2 Literature review: In this chapter, the theoretical foundation and conceptual framework of the study were established. The chapter provided clear definitions of key concepts and terms. Additionally, systematic reviews were presented, along with a comprehensive checklist of digital twins and construction projects in Saudi Arabia.

Chapter 3 Methodology: In this chapter, the study's research process and methodologies were outlined. The research paradigm, research design, methods for data collection, and techniques for data analysis were defined and described. The chapter also discussed the research methods employed and the analytical approaches utilized.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The construction industry, characterized by its complexity, requires careful coordination of various processes and stakeholders throughout a project's lifecycle. From the planning phase to execution and delivery, construction projects face both planned and unforeseen challenges that can significantly affect outcomes, accompanied by changes in stakeholders and processes within a dynamic environment. The factors that have the most impact on project performance and lead to successful completion are known as critical success factors. It is crucial for project managers to accurately identify these key factors in order to allocate appropriate resources to them. Researchers have identified several critical success factors, such as employer and project manager satisfaction, schedule and budget performance, effective programming of construction activities, quality performance, control system, and design planning. Among these factors, the ability to accurately and quickly assess project progress is crucial to effective project management. A precise evaluation of progress enables managers to make necessary adjustments and achieve project objectives [15-17].

While critical success factors are central to understanding project performance, the role of emerging technologies in transforming construction processes cannot be overlooked. Digital tools such as Digital Twin technology are revolutionizing the construction sector by enabling more accurate and efficient project execution. These technologies enhance the ability to track progress, optimize resource allocation, and manage project risks, thereby contributing to improved outcomes. Digital Twin technology, for example, offers a virtual representation of the physical construction project, which can be used for real-time

monitoring and predictive analysis, helping to minimize delays and cost overruns. Many researchers have provided definitions of Digital Twin technology, each emphasizing different aspects of its applications and functionalities within various industries, including construction. Table 1 presents a summary of key definitions.

In addition to the technological advancements, project managers must also consider the broader context of construction projects, including regulatory frameworks, market conditions, and the evolving expectations of stakeholders. The integration of these factors requires a holistic approach that includes not only the traditional success factors but also the role of innovation and technology adoption in shaping the future of construction management. This chapter explores these aspects, examining the current state of the construction industry, the development of critical success factors, and the implications of emerging technologies like Digital Twins in enhancing construction project outcomes.

Table 1: Definitions of Digital Twins

Source	Definition of Digital Twin
Glaessgen and Stargel, [18]	A Digital Twin represents a highly detailed, multi-physics, multi-scale, probabilistic simulation of a vehicle or system. It integrates the best available physical models, real-time sensor data, fleet history, and other relevant information to replicate the lifecycle of its physical counterpart. This ultra-realistic digital representation accounts for key interdependencies among various vehicle systems, enabling precise mirroring and advanced analytics to optimize performance and predict future behavior.
Lee et al. [19]	A cloud-based coupled model of the real machine integrates data-driven analytical algorithms with available physical knowledge to simulate its health condition accurately. This approach combines real-time data and theoretical insights to monitor and predict the machine's performance effectively.
Grieves [4]	A digital replica of the produced output or result, typically used to track or visualize the creation process and its final state.
Rosen et al. [20]	Highly detailed models that represent the current state of a process and its interactions with the real-world environment, capturing its behavior with high accuracy.
Schluse and Rossmann,[2]	Virtual representations of real-world objects, equipped with communication capabilities, serve as smart objects acting as intelligent nodes within the Internet of

	Things (IoT) ecosystem. These virtual substitutes are integral components that facilitate data exchange and enable smart interactions in various IoT services.
Canedo, [22]	A digital replica of a real-world object that emphasizes the object itself, capturing its key characteristics and attributes in a virtual format. This representation is primarily focused on accurately mirroring the physical object's properties and behaviors.
Schroeder et al., [23]	Virtual replica of real products in context of Cyber-Physical Systems.
El Saddik [24]	Digital replicas of both living and non-living entities that facilitate the seamless transmission of data between the physical and virtual realms. These digital representations enable continuous interaction and data exchange, bridging the gap between real-world objects and their virtual counterparts.
Zhuang et al. [26]	A dynamic virtual model that accurately mirrors its physical counterpart in the real world, simulating its characteristics, behavior, lifecycle, and performance in real-time. This digital twin ensures full consistency with physical entity, allowing for timely analysis and optimization based on its virtual representation.
Qi and Tao [25]	Digital models of physical objects are created to replicate and simulate their behaviors within real-world environments. These virtual representations enable the study and analysis of how the physical objects interact with their surroundings, providing insights into their performance, lifecycle, and potential improvements.

2.2 Digital twins' application

Digital twins have become a transformative technology across industries, providing innovative solutions for enhancing efficiency, productivity, and decision-making. By creating virtual replicas of physical systems, they enable real-time monitoring, analysis, and simulation. The application fields of digital twins are diverse, with significant implications for numerous sectors. Shi [27] In the manufacturing sector, realize that digital twins are creating virtual replicas of machines, production lines, and even entire factories, this technology is key in enabling predictive maintenance, optimizing manufacturing processes, and designing efficient production systems, aligning with the principles of Industry 4.0. On the other hand, Zang found that the development of smart cities significantly benefits from digital twins. Offering real-time monitoring and management of urban infrastructures such as transportation networks, energy grids, and public services, playing a crucial role in modern urban planning and management [28].

Researchers like Leng realized that in the healthcare sector, digital twins are transforming personalized medicine and patient care. By creating virtual models of individual patients, they allow healthcare professionals to simulate treatments, monitor health conditions, and predict the progression of diseases more accurately [29]. Moreover, Buzatu investigate The aerospace industry utilizes digital twins to simulate aircraft performance, monitor equipment health, and enhance maintenance processes, this application is instrumental in reducing downtime and improving safety standards in the sector [30]. In energy and utilities, Bessa did research and realized digital twin's applications in power plants, grids, and renewable energy sources. They are utilized to optimize energy production, distribution, and consumption, thereby contributing to broader sustainability goals [31].

Within the construction industry, digital twins are enhancing building design, construction, and facility management. Fostering better collaboration among stakeholders and help reduce construction errors, leading to more efficient project execution [32]. Digital twins also play a role in environmental studies by simulating ecosystems and climate models. This is particularly important in understanding and mitigating the impacts of climate change, providing valuable insights for environmental conservation efforts [33]. In the realm of supply chain management, digital twins optimize operations by offering real-time visibility into product movement. This technology helps companies streamline logistics, reduce costs, and improve inventory management, leading to more efficient supply chain processes [6].

The above applications are just a glimpse of the potential of digital twins in various sectors. As technology continues to advance and the concept of digital twins matures, we can anticipate even more innovative and impactful uses across industries, ultimately driving efficiency, sustainability, and better decision-making.

2.2 Digital twins in the construction industry

The adoption of digital twin (DT) technology is transforming the construction industry, demonstrating its ability to address the complexities of modern construction projects and ushering in a new era of efficiency and precision. The integration of DTs with Building Information Modelling (BIM), as highlighted by Thompson and Chan [82], has advanced project visualization and management capabilities, offering real-time updates and multidimensional analyses. This combination enhances decision-making processes across all phases of construction, from design to the management of completed structures. Garcia and Fernandez [83] provide empirical evidence showing that DTs not only expedite project delivery timelines but also reduce resource wastage, thus supporting sustainability goals. Practical applications of DTs are well-documented in case studies such as the NeoPlex Tower in Germany, where real-time monitoring reduced errors and improved adaptability to changing conditions on-site [84]. Another example includes the Golden Gate Bridge, where predictive maintenance strategies using DTs enhanced safety and extended the lifespan of critical infrastructure [85]. These studies underline the significant role of DTs in operational efficiency and risk mitigation.

Zhu [81] explored the analytic potential of DTs, demonstrating how predictive analytics applied to DT-generated data structural issues, facilitating cost-effective and timely interventions. Similarly, Applied Machine Learning integrated DT data to optimize scheduling and resource allocation, achieving notable improvements in construction efficiency.

Despite their benefits, DT adoption in the construction sector faces challenges, particularly concerning cybersecurity and data privacy. Esposito and Rossi [87] highlighted

vulnerabilities in DT systems, recommending robust security frameworks to mitigate risks. They also discussed the ethical implications of DT use, emphasizing the need for stringent guidelines to protect data privacy and prevent misuse. These concerns align with findings from Henseler et al., who advocate for the development of governance frameworks to ensure ethical and sustainable technology integration [86]. Collectively, these studies stress the necessity of a balanced approach to adopting digital twins in construction. This strategy should capitalize on its technological advantages while addressing associated challenges to achieve a responsible and sustainable transformation of the industry.

2.4 Construction Projects in Saudi Arabia

The construction sector in Saudi Arabia has undergone substantial expansion and evolution over time. This theory seeks to establish a conceptual framework for comprehending the intricacies, obstacles, and potential prospects associated with construction ventures in the Kingdom of Saudi Arabia. Furthermore, construction plays a pivotal role in the Saudi Arabian economy, with the Gross Domestic Product (GDP) generated from the construction sector surpassing SAR 29 billion in the fourth quarter of 2017, solidifying its position as one of the most significant contributors in the region [34]. The aggregate worth of construction contracts granted in Saudi Arabia during 2017 stood at approximately USD 24 billion. While the initiation of some of these contracts has been deferred or held up due to recent declines in oil prices and the government's financial reform initiatives, it remains indisputable that the construction sector in Saudi Arabia continues to be a significant driver of domestic economic advancement and expansion. Saudi construction contractors represent the most substantial and profligate customers in diverse sectors of the economy, including materials, equipment, and logistics services. Certainly, there is an undeniable necessity to

enhance the performance and productivity of Saudi construction contractors, alongside the establishment of methods for evaluating their performance. The requirement arises due to the observation that, despite the substantial contract values assigned to construction contractors, a considerable number of significant projects are still being completed with apparent flaws, whether in terms of specifications or functionality [35].

The Saudi Ministry of Housing is gearing up to launch an ambitious endeavor aimed at constructing 100,000 housing units in Riyadh within the upcoming five to seven years [35]. Additionally, the Saudi government has already granted numerous contracts for extensive infrastructure projects that cater to diverse regions throughout the kingdom. In addition to the construction and engineering sectors in Saudi Arabia are on the verge of experiencing significant shifts in how business operations are carried out. In certain sectors, these changes are already underway. The sustained success of any contractor in the Saudi market hinges greatly on their capacity to enhance operational efficiency and elevate the quality of products and services provided to clients [35]. Saudi Arabia draws upon existing literature and research findings to elucidate key principles and factors that shape the construction landscape in Saudi Arabia.

1. Economic Drivers: At the core of construction projects in Saudi Arabia are economic drivers, notably the country's reliance on oil revenues. The theory posits that fluctuations in oil prices significantly impact government budgets, which, in turn, influence the level of investment in construction and infrastructure projects [36].

2. Vision 2030: Saudi Arabia's Vision 2030 serves as a guiding framework for the construction sector. This ambitious plan aims to diversify the economy, reduce dependence on oil, and enhance infrastructure. The theory asserts that Vision 2030 has ushered in a new era of development, with a focus on mega-projects and urban transformation [37].

3. **Regulatory Environment:** The regulatory environment plays a pivotal role in shaping construction projects. The theory highlights the importance of government regulations, permits, and compliance standards in ensuring project quality, safety, and sustainability [38].
4. **Labor Force:** A significant factor in Saudi Arabia's construction industry is the composition and availability of the labor force. The theory emphasizes the reliance on foreign labor, labor market dynamics, and the impact of labor policies on project timelines and costs [39].
5. **Technological Advancements:** The adoption of advanced technologies, such as Building Information Modeling (BIM) and construction management software, is a key component of construction projects in Saudi Arabia. The theory suggests that technology enhances project efficiency, collaboration, and data-driven decision-making [40].
6. **Sustainability and Green Building:** The theory emphasizes the growing importance of sustainability and green building practices in Saudi Arabia's construction projects. Sustainability initiatives align with Vision 2030 goals and focus on energy efficiency, environmental conservation, and sustainable design [41].
7. **Infrastructure Development:** Construction projects in Saudi Arabia span various domains, including transportation, healthcare, education, and tourism. The theory suggests that infrastructure development is crucial for economic diversification and improving the quality of life for Saudi citizens [42].
8. **Public-Private Partnerships (PPP):** The theory acknowledges the increasing use of PPP models to finance and deliver construction projects. PPPs are seen as a means to leverage private sector expertise and resources in executing large-scale projects [43].

In conclusion, the theory of construction projects in Saudi Arabia underscores the multifaceted nature of this sector, influenced by economic, regulatory, technological, and societal factors. As the Kingdom continues its journey towards economic diversification and development, the construction industry will remain a central driver of transformation and progress. This theory provides a foundation for comprehending the complex interplay of forces that shape construction projects in Saudi Arabia.

2.5 Project Success Factors

Project success factors are the critical elements, conditions, and variables that significantly influence the achievement of a project's objectives within predefined parameters of scope, time, cost, quality, and stakeholder satisfaction. These factors serve as key determinants that directly contribute to the positive outcome and effectiveness of a project. Project success factors vary based on the nature of the project, industry, and organizational context. They are often interdependent and require a holistic approach to management. Recognizing and prioritizing these factors enhances the likelihood of achieving project goals and delivering value to stakeholders. In the context of project management, success factors can be defined as the elements that exert influence, contribute to, and ultimately shape the outcome of a project's success. Cooke-Davies and De Wit [45], [47] respectively, mention further elaborate that these success factors encompass the inputs integrated into the project management system, which play a direct or indirect role in steering the project toward its successful achievement.

Success factors can be categorized into two primary groups. The first category comprises hard factors, which are characterized by their concrete, measurable, and goal-oriented nature. In contrast, the second category consists of soft factors, which are more subjective,

intangible, and challenging to quantify [46]. Numerous research endeavors have concentrated on identifying the factors contributing to project success, particularly in the context of construction projects. These studies have systematically extracted critical success factors from existing literature and categorized them into two main groups: internal factors and external factors [44].

2.5.1 Construction Project Success Criteria

The success of construction projects is a complex and multifaceted concept, influenced by various factors and objectives. Defining and measuring project success is essential for evaluating project performance, identifying areas for improvement, and guiding decision-making throughout the project lifecycle. This literature review provides an overview of the key success criteria used to assess construction project success, encompassing multiple dimensions such as time, cost, quality, safety, and stakeholder satisfaction [50]. Employed the Pinto criteria or project success dimensions in her research, which closely aligns with the current study [51]. These criteria have been compiled in Table 2 to enhance comprehension of the evolution of success metrics over time.

Table 2: Project Success Measures

Item	Measures
The project is on time	Time
The project is within budget	Cost
The project is working	Technical
Problem is solved	Validity
Customer is using the project	Organizational
Client is using the product or service of the project	

The project functional purpose is achieved	Validity
Specified benefits of the project were attained	Organizational Effectiveness
The project improved decision making for the client	
The project has impacted the users positively	
The results of this project improved performance over the way clients used to perform these activities.	

Furthermore, a newer classification of success metrics by [52] has categorized them into dimensions, which include Project efficiency, Impact on the customer, Business Success, and Preparing for the Future. These dimensions are presented in Table 3.

Table 3: Performance Dimensions of project success

Performance Dimension-Measures	
1. Project-efficiency	schedule-goal was met
	Budget-goal was met
2. Customer-impact	functional requirements met
	technical specifications met
	customer-needs achieved
	Resolving customer's problem
	The customer is using service
	Customer-satisfaction
3. Business-Success	Commercial-Success
	Creating market-share
4. Preparing-for-the Future	new market created
	Creating new-product-line

2.5.2 key success criteria to assess the construction project

1. **Project Management and Leadership:** Effective project management practices and strong leadership are fundamental to project success [53]. Skilled project managers can navigate complexities, manage resources, and maintain project focus.
2. **Scope Definition and Management:** Clearly defining project scope and effectively managing scope changes is essential [54]. Poor scope control can lead to delays and cost overruns.
3. **Budget and Cost Control:** Staying within budget is a critical success factor [48]. Cost overruns can jeopardize project viability [56].
4. **Schedule and Time Management:** Adherence to project schedules is vital [57]. Delays can escalate costs and affect stakeholders' confidence.
5. **Quality Assurance and Control:** Ensuring that the final product meets quality standards is crucial [58]. Subpar quality can lead to rework and legal issues.
6. **Risk Management:** Effective risk identification and mitigation are essential [59]. Unmanaged risks can result in project failure.
7. **Stakeholder Engagement:** Managing stakeholder expectations and ensuring their involvement is critical [60]. Satisfied stakeholders often correlate with project success.
8. **Communication and Information Flow:** Open and effective communication among project team members is key [61]. Miscommunication can lead to misunderstandings and conflicts.
9. **Regulatory Compliance:** Adherence to legal and regulatory requirements is vital [62]. Non-compliance can lead to fines and project delays.

10. Resource Allocation: Proper allocation of resources, including labor, materials, and equipment, is necessary [63]. Resource shortages can impede progress.
11. Safety and Health: Ensuring a safe and healthy work environment is essential [64]. Accidents can result in project delays and legal consequences.
12. Environmental Sustainability: Addressing environmental concerns and adopting sustainable practices is increasingly important [65]. Green building standards can impact project success [55] [58].
13. Technology and Innovation: Embracing innovative construction technologies can enhance efficiency and competitiveness [66]. Failure to adapt can hinder project success.
14. Client Satisfaction: Meeting client expectations and ensuring client satisfaction is a key success criterion [67]. Happy clients often lead to future opportunities.
15. Contractual Arrangements: The choice of contract type and effective contract management can influence project success [68]. Ambiguous contracts can lead to disputes.
16. Market Conditions: Economic and market conditions can affect project viability and profitability. Projects initiated during economic downturns may face challenges.
17. Political and Social Factors: Political stability and social factors can impact project feasibility and execution [56].
18. Post-Project Evaluation: Conducting a thorough review of the project after completion to identify lessons learned and areas for improvement. [53]
19. Stress and Crisis Management: Effectively handling stress and unforeseen crises that may impact the project [59].
20. Project Closure (proper completion): Completing the project efficiently, including documentation, final evaluations, and handover processes [67].

21. Vendor Management: Managing relationships with suppliers and contractors to ensure timely delivery of services and materials [60].

22. Change Management: Being flexible and adaptable to changes, and efficiently managing these changes during the project [88].

Other Success Criteria:

Innovation: The extent to which a project introduces and incorporates innovative technologies, methods, or processes. [69]. Environmental Sustainability: The degree to which a project minimizes its impact on the environment and promotes sustainable practices. [65]. Legal and Regulatory Compliance: The adherence to legal and regulatory requirements throughout the project lifecycle [58]. Organizational Objectives: The alignment of project outcomes with the strategic goals and objectives of the organization or client.

In conclusion, construction project success is a multifaceted concept influenced by a myriad of factors. A holistic approach to project management, considering these factors and their interplay, is essential for achieving successful project outcomes.

Table 4 Projects success factors

#	Critical Success Factor	Sources
1	Project Management and Leadership	[53]
2	Scope Definition and Management	[54]
3	Budget and Cost Control	[48], [56], [89]
4	Schedule and Time Management	[57], [88]
5	Quality Assurance and Control	[58], [60]
6	Risk Management	[59]

7	Stakeholder Engagement	[60]
8	Communication and Information Flow	[61]
9	Regulatory Compliance	[62]
10	Resource Allocation	[63]
11	Safety and Health	[64]
12	Environmental Sustainability	[65], [55],[58]
13	Technology and Innovation	[66], [69]
14	Client Satisfaction	[67]
15	Contractual Arrangements	[68]
16	Market Conditions	[58]
17	Political and Social Factors	[56]
18	Post-Project Evaluation	[53]
19	Stress and Crisis Management	[59]
20	Project Closure (proper completion)	[67]
21	Vendor Management	[60]
22	Change Management	[88]

2.6 Digital Twin Characteristics

Digital Twins (DTs) are advanced virtual models that replicate physical assets, enabling real-time data integration, predictive analytics, and lifecycle management across industries. Their key characteristics include precise representation and modeling, real-time data synchronization, and the ability to simulate scenarios for optimizing processes and identifying risks. Interoperability with systems like BIM and IoT ensures seamless integration and scalability, while their lifecycle support enhances asset efficiency from

design to maintenance. Digital Twins also provide robust security measures for data privacy and serve as collaborative platforms for stakeholders, fostering better communication and decision-making. These features collectively highlight their transformative role in enhancing operational efficiency and sustainability in sectors like construction and manufacturing.

1. Virtual Representation

Digital twins create a virtual replica or model of a physical object, system, or process. This virtual representation is a detailed and accurate reflection of the physical entity, capturing its geometry, behavior, and attributes. These models are typically built using various technologies such as 3D modeling, computer-aided design (CAD) data, sensor data, and simulation algorithms [18]. Digital twins enable architects, engineers, and construction professionals to create highly detailed and accurate virtual models of buildings and infrastructure [77]. These models can be used for in-depth design analysis, simulations, and clash detection. This level of precision in the design phase helps identify potential issues early, reducing the likelihood of costly errors during construction. Digital twins can help streamline project schedules and budgets. By reducing errors, optimizing workflows, and enabling better resource allocation, construction projects are completed more efficiently, which can lead to cost savings [78].

2. Real-Time Data Integration

Digital twins are continuously updated with real-time data from sensors, IoT devices, and other sources attached to the physical object they represent. This real-time data integration allows for a dynamic and current view of the physical entity's state, enabling rapid responses to change and events [71]. Real-time data integration allows construction teams to access up-to-the-minute information about various aspects of the project, such as progress, resource

allocation, and safety conditions. This data empowers project managers and stakeholders to make informed decisions promptly [79]. Real-time data integration helps construction teams optimize the allocation of resources such as labor, equipment, and materials. By tracking resource usage and availability in real-time, teams can make adjustments to ensure efficient resource utilization [80]. Real-time data integration helps identify potential risks and safety concerns in real-time. By analyzing data from various sources, construction teams can implement safety measures and protocols to mitigate risks and ensure a safer work environment [17]. In addition, Real-time data integration helps project owners and clients stay informed about project progress and performance. This transparency enhances client satisfaction and trust in the construction process [81].

3. Two-Way Communication

Two-way communication within the context of digital twins means that data can flow in both directions—between the physical construction site and the virtual twin. This communication is facilitated through technologies like AR (Augmented Reality), IoT devices, and cloud-based platforms. The bidirectional communication aspect of digital twins means they not only passively receive data but can actively send commands and instructions back to the physical object. This interaction enables remote control, adjustments, and interventions, making digital twins valuable for remote monitoring and maintenance [72].

4. Simulation and Analysis

Digital twins facilitate the creation of simulations that mimic the behavior of the physical entity. These simulations can be run under different scenarios and conditions. Analysis of these simulations aids in understanding how the physical entity operates and how changes in parameters might affect its performance [2].

5. Historical Data Storage

Digital twins store historical data over time, creating a historical record of the physical entity's behavior, performance, and changes. This historical data is essential for trend analysis, anomaly detection, and long-term performance evaluation [73].

6. Interoperability

Digital twins are designed to work seamlessly with other software and systems, enabling integration with a wide range of technologies. This interoperability ensures that digital twins can fit into larger ecosystems, such as manufacturing systems, supply chain management, or smart infrastructure [74].

7. Predictive Analytics

By leveraging historical and real-time data, digital twins employ advanced analytics and machine learning to predict future behaviors, failures, or maintenance needs. Predictive analytics help organizations move from reactive to proactive decision-making and maintenance strategies [75].

8. Security and Privacy

Security measures are crucial to protect the integrity and confidentiality of data within digital twins, especially in critical applications like healthcare, industrial control, and defense. Measures include encryption, access controls, and authentication to safeguard data from unauthorized access or tampering [76]. These characteristics collectively enable digital twins to serve a wide range of applications, from optimizing manufacturing processes and

predictive maintenance in industry to improving patient care in healthcare and creating resilient smart cities. They provide a bridge between the physical and digital worlds, allowing for more informed decision-making and efficient operations.

2.7 Literature Review Summary and Identification of Research Gap

The literature on Digital Twin (DT) technology underscores its transformative role across industries, including construction, manufacturing, and urban management. Digital Twins serve as real-time virtual replicas of physical assets, integrating advanced modelling, real-time data synchronization, and predictive analytics to optimize project outcomes [2]. Research highlights their ability to enhance lifecycle management, foster collaboration among stakeholders, and improve operational efficiency. Specific functionalities, such as interoperability with BIM and IoT systems, advanced security protocols, and their role in predictive maintenance, have been explored extensively, demonstrating their potential to address challenges like resource allocation, cost management, and sustainability [6]. However, several gaps persist in the current body of knowledge. First, while the theoretical foundations of Digital Twins are well-established, empirical research validating their impact on project success in the construction industry remains limited, particularly in the context of developing markets like Saudi Arabia. Most studies focus on applications in manufacturing or developed economies, leaving a gap in understanding how DTs address the unique challenges of construction projects, including complex workflows, fragmented communication, and compliance with regional regulations [18]. Second, existing frameworks for implementing Digital Twins often lack specificity regarding the functional capabilities of DTs such as representation, predictive analytics, and security measures and their direct influence on critical project outcomes, including efficiency, stakeholder

satisfaction, and business success. Few studies provide comprehensive models that evaluate these functionalities in relation to project management and validate their applicability through real-world case studies.

Lastly, the rapidly evolving nature of Digital Twin technology presents another gap. As new advancements emerge, such as AI-driven simulation and cloud-based collaboration, there is a need for updated research that captures the full scope of DT applications and adapts existing frameworks to align with these innovations. This study aims to address these gaps by developing and empirically validating a framework that assesses the impact of Digital Twin functionalities on project success, focusing on Saudi Arabia's construction sector. By combining theoretical insights with practical case studies, this research contributes to the body of knowledge by offering actionable recommendations for leveraging DT technology to enhance project performance, stakeholder collaboration, and sustainability in construction projects.

CHAPTER 3

METHODOLOGY

3.1 Overview

This chapter discusses the research methodology used to investigate the influence of Digital Twins in construction organizations in Saudi Arabia. It explores the contribution of Digital Twins to project, organizational, and Project Management maturity. The study aims to enhance our understanding of how Digital Twins operate within the organizational context and how organizations leverage this technology to achieve their objectives. Furthermore, this study seeks to enhance the current understanding and knowledge regarding the successful utilization of digital twins.

The primary objective is to identify the main impact of digital twins on their respective organizations and assess the satisfaction level of their stakeholders. The research steps consist of stages, as illustrated in Figure 1. These stages involve conducting an extensive literature review to identify the roles and functions performed by Digital Twins, identifying measurable performance dimensions, and designing the research questionnaire. The survey is distributed to groups or populations. The population consists of experts in the construction industry who are asked to complete a modified version of the survey tailored to fit the industry's context. The population addresses the key research question: "The impact of Digital Twins with its performance on construction projects? and how satisfied are the stakeholders?" To assess this, a standardized survey tool used in quality management, measuring the impact of Digital Twins and the satisfaction level of the stakeholders will be adopted. This tool evaluates stakeholder perceptions and expectations, providing insights into their satisfaction with the service provided by Digital Twins.

To achieve these objectives, a comprehensive and systematic research methodology has been devised. This chapter outlines the various components of the methodology, including the research hypothesis, data collection methods, data analysis techniques, and the overall research framework. Each of these elements has been carefully designed to ensure the rigor and validity of the study findings. Furthermore, data analysis techniques such as statistical analysis, thematic analysis, and content analysis will be employed to analyze the collected data. These analytical methods will enable the identification of key patterns, themes, and relationships among the critical success factors and their impact on the implementation of the digital twins. In this chapter, an outline is given of the research methodology utilized in this study. By following a systematic and rigorous approach, this research aims to shed light on the digital twin, and how it will impact construction projects and contribute to the advancement of project management practices.

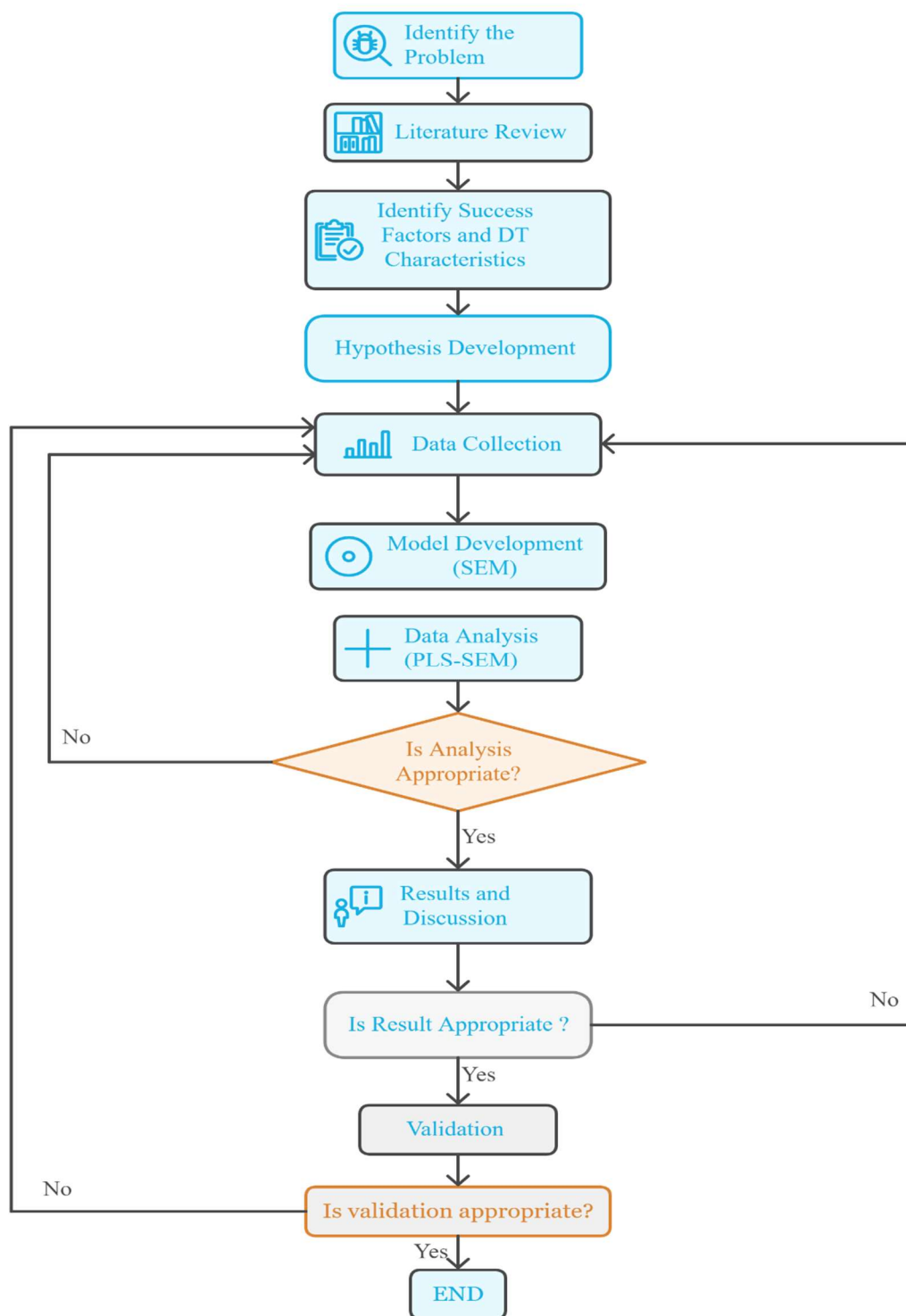


Figure 1: Research Framework

3.2 Digital twins' characteristics (Independent Variables)

In the context of this study, Digital Twin technology is explored through four key characteristics, referred to as independent variables, that contribute to improving construction project outcomes, particularly in Saudi Arabia. These four roles of Digital Twins are integral to understanding how this technology can optimize project management and execution within the construction industry, which is still in the process of adopting these advanced technologies. These characteristics are treated as independent variables because they directly influence the dependent variables. They are categorized into latent variables or constructs. The ultimate list comprises 8 digital twin function's indicators, denoted as X1 to X8 (representing the independent variables).

Table 5: Independent Variables

Label	Function/Measures	Variables
X1	Virtual Representation	Representation and Modeling
X2	Simulation and Analysis	
X3	Real-Time Data Integration	Data Handling and Integration
X4	Historical Data Storage	
X5	Two-Way Communication	Communication and Interaction
X6	Interoperability	Functional Capabilities and Security
X7	Predictive Analytics	
X8	Security and Privacy	

3.3 Project success factors (dependent Variables)

To assess the influence of digital twins in construction and other industry organizations, this study aimed to investigate the effect of digital twin roles or functions on project success or performance. Several metrics were organized into groups referred to as dimensions or latent constructs. Table 5 displays the measurable variables (Y1 to Y14) categorized into four groups of dependent.

Table 6: Dependant variables

Label	Variable Name	EndogenousConstructs
Y1	Project Management and Leadership	Project Management and Leadership
Y2	Scope Definition and Management	Project Efficiency
Y3	Budget and Cost Control	
Y4	Schedule and Time Management	
Y5	Quality Assurance and Control	
Y6	Resource Allocation	
Y7	Safety and Health	
Y8	Environmental Sustainability	
Y9	Technology and Innovation	
Y10	Change management	
Y11	Team management	
Y12	Stakeholder Engagement	Stakeholder Management & Satisfaction
Y13	Communication and Information Flow	
Y14	Client Satisfaction	
Y15	Commercial Success (Profit, return on investment)	Business Success

3.4 Hypothesis

To achieve the objectives of this study, a conceptual framework was developed, and hypotheses were formulated based on an extensive literature review and expert opinions. These hypotheses aim to address the first research question by examining the relationships between Exogenous Constructs (factors influencing the model) and Endogenous Constructs (outcomes of the model), as outlined in Table 3.6. It has been hypothesized, based on previous research, that the presence of Digital Twin technology has a positive impact on project success. As the implementation of Digital Twin systems increases, it is expected that project success will correspondingly improve. This relationship aligns with findings from various studies that suggest the availability of Digital Twin technology contributes to more successful project outcomes.

Hypothesis H0: The functions performed by Digital Twins have a positive impact on project Success. The motivation for the main hypotheses and the sub-hypotheses was to investigate the impact of Digital Twins' characteristics/ functions on project success.

Sub-hypotheses for Category 1:

H1: The utilization of Digital Twins in Representation and Modelling of the project has a positive impact on Project Management and Leadership.

H2: The utilization of Digital Twins in Representation and Modelling of the project has a positive impact on Project Efficiency.

H3: The utilization of Digital Twins in Representation and Modelling of the project has a positive impact on Stakeholder Management & Satisfaction.

H4: The utilization of Digital Twins in Representation and Modelling of the project has a positive impact on Business Success.

Sub-hypotheses for Category 2:

H5: Development of Digital Twin-based Data Handling and Integration has a positive impact on Project Management and Leadership.

H6: Development of Digital Twin-based Data Handling and Integration has a positive impact on Project Efficiency.

H7: Development of Digital Twin-based Data Handling and Integration has a positive impact on Stakeholder Management & Satisfaction.

H8: Development of Digital Twin-based Data Handling and Integration has a positive impact on Business Success.

Sub-hypotheses for Category 3:

H9: Participation of Digital Twins in Communication and Interaction has a positive impact on Project Management and Leadership.

H10: Participation of Digital Twins in Communication and Interaction has a positive impact on Project Efficiency.

H11: Participation of Digital Twins in Communication and Interaction has a positive impact on Stakeholder Management & Satisfaction.

H12: Participation of Digital Twins in Communication and Interaction has a positive impact on Business Success.

Sub-hypotheses for Category 4:

H13: Digital Twins' support for Functional Capabilities and Security has a positive impact on Project Management and Leadership.

H14: Digital Twins' support for Functional Capabilities and Security has a positive impact on Project Efficiency.

H15: Digital Twins' support for Functional Capabilities and Security has a positive impact on Stakeholder Management & Satisfaction.

H16: Digital Twins' support for Functional Capabilities and Security has a positive impact on Business Success.

These hypotheses are evaluated using Structural Equation Modeling (SEM), a complex data analysis technique that examines the relationships between dependent and independent variables within a set of constructs. SEM helps determine how exogenous variables (independent constructs) influence endogenous variables (dependent constructs), allowing for a comprehensive understanding of the model. The results of this analysis, as illustrated in Figure 5, help validate, modify, or reject the hypotheses based on empirical data.

3.5 Structural Equation Modeling Development

Structural Equation Modelling (SEM) is an essential analytical approach in social science research, enabling the exploration and validation of complex relationships between variables. In this study, Partial Least Squares Structural Equation Modelling (PLS-SEM) was applied to assess the hypothesized relationships within the proposed framework, focusing on the impact of Digital Twin features on construction project success. This method was chosen for its suitability in handling complex models with multiple constructs,

particularly when dealing with small sample sizes or data that may not meet normality assumptions. Using SmartPLS software, the study followed a systematic process: specifying the structural model based on the research framework, inputting and analyzing the collected survey data, and estimating the path model to evaluate direct and indirect relationships. The analysis included assessing the measurement model for reliability and validity through composite reliability, Cronbach's alpha, and average variance extracted (AVE). The structural model was then validated by examining R^2 values, effect sizes (f^2), and path coefficients. This comprehensive application of PLS-SEM provided valuable insights into the relationships between the constructs, supporting the empirical validation and refinement of the Digital Twin implementation framework for enhancing project success in Saudi Arabia's construction sector.

The use of structural analysis plays a critical role in developing, exploring, and validating research findings, making it one of the most valuable tools for social science researchers over the years. Partial Least Squares Structural Equation Modeling (PLS-SEM) has emerged as one of the leading second-generation statistical methods for multivariate analysis. In comparison, Covariance-Based Structural Equation Modeling (CB-SEM) was the dominant technique for publishing research in social sciences until 2010. However, more recently, PLS-SEM has become increasingly popular, with a growing number of publications surpassing those of CB-SEM in many fields of research [90].

Currently, PLS-SEM has gained widespread acceptance across various fields, including human resource management [91], marketing management [92], organizational management [93], operations management [94], international management [95], strategic management [96], supply chain management [97], hospitality management [98], tourism and travel management [99], management accounting [100], and management information systems. Additionally, this technique is increasingly applied in disciplines such as economics, engineering, environmental sciences, medicine, political sciences, and psychology [101]. More recently, PLS-SEM has been adopted within the banking and finance sector [102]. Furthermore, the methodology has been featured in a variety of publications, including special issues of academic journals, textbooks, and edited volumes, reflecting its growing influence and applicability across diverse research areas and disciplines.

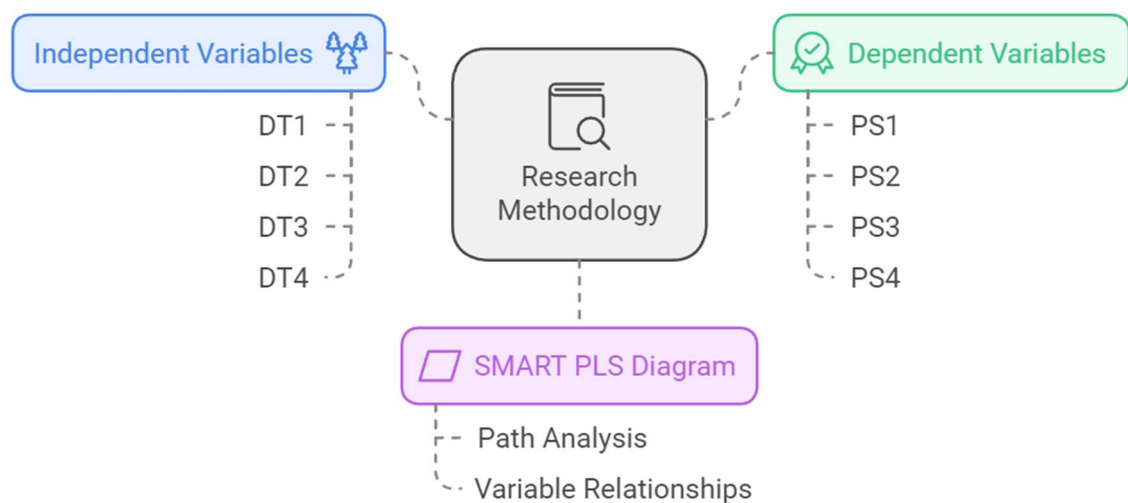


Figure 5: Research methodology using SEM PLS

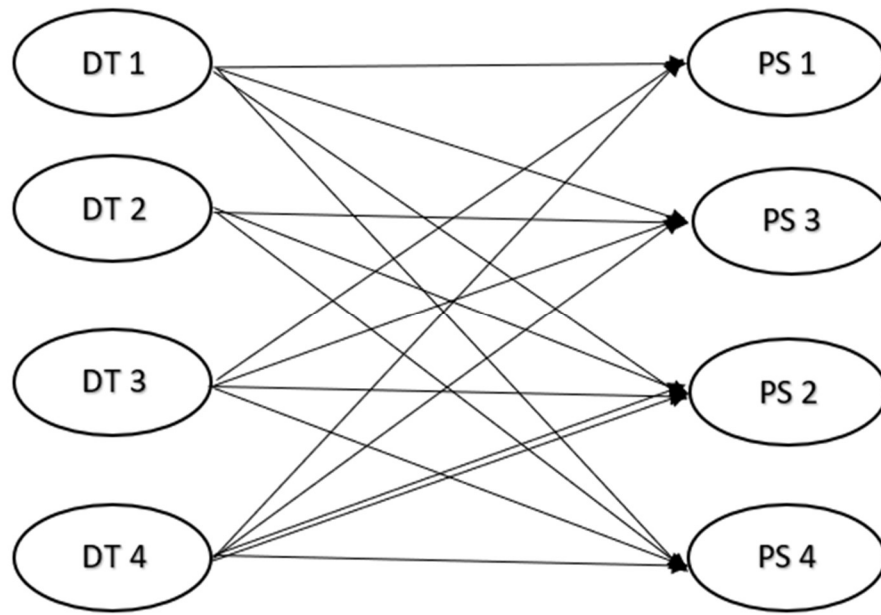


Figure 6: Theoretical model

SmartPLS is a software with an intuitive graphical user interface (GUI) designed for variance-based Structural Equation Modeling (SEM), specifically using the Partial Least Squares (PLS) path modeling method [103], [104]. It facilitates the estimation of PLS path models with latent variables (constructs) through the PLS-SEM algorithm. Additionally, it's offers a range of evaluation criteria to assess the quality of results, including the assessment of structural models, reflective and formative measurement models, and model fit measures [105]. These features make SmartPLS a powerful tool for conducting advanced SEM analysis in various research fields. In addition to supporting the PLS algorithm, bootstrapping, and blindfolding procedures, SmartPLS also facilitates a range of additional statistical analyses. These include multi-group analysis, confirmatory tetrad analysis, importance-performance map analysis, prediction-oriented segmentation, and permutation testing [106]. Another notable advantage of SmartPLS is its cross-platform compatibility, as it is developed in Java, allowing it to run on different operating systems, including Windows and Mac. As a result, SmartPLS has become a widely recognized and standard

software for the PLS-SEM statistical technique. This is why it was chosen for this research study, specifically utilizing version SmartPLS 3 for the empirical analysis in this thesis.

Historically, researchers in structural equation modeling primarily relied on univariate (analyzing a single variable) and bivariate (examining relationships between two variables) methods to identify patterns and relationships within data. However, analyzing more complex relationships requires multivariate analysis, which involves multiple variables and utilizes statistical techniques such as factor analysis, cluster analysis, logistic regression, multiple regression, and multidimensional scaling. These multivariate methods are often referred to as first-generation statistical techniques [107]. These methods can be further categorized into exploratory and confirmatory approaches, depending on the nature of the analysis. Confirmatory analysis involves testing hypotheses based on theories or concepts that have been established a priori. Examples of first-generation statistical methods that fall under this category include logistic regression, multiple regression, analysis of variance, and confirmatory factor analysis. These methods aim to validate or confirm predefined relationships between variables [107]. On the other hand, exploratory analysis is used when there is limited or no prior knowledge of the relationships between constructs or variables. This approach seeks to identify patterns or relationships within the data without predetermined hypotheses. Examples of first-generation statistical methods for multivariate analysis in the exploratory category include cluster analysis, multidimensional scaling, and exploratory factor analysis [107].

In the past, social science researchers commonly employed first-generation statistical techniques. However, to address the limitations of these methods, there has been a significant shift toward second-generation techniques, primarily Structural Equation Modelling (SEM). SEM is recognized as a sophisticated statistical method [108] due to its

ability to evaluate relationships between constructs, including both latent (unobserved) and indicator (observed) variables, while also accounting for measurement error in observed variables [109]. SEM encompasses two main approaches for estimating model relationships: covariance-based SEM (CB-SEM) and component-based or Partial Least Squares SEM (PLS-SEM). Initially known as PLS path modelling, the term PLS-SEM is still used to describe this method [110]. This transition to second-generation techniques represents a major advancement in the field, offering enhanced analytical power and flexibility over traditional methods.

3.5.1 PLS Path Modeling

In this section, a detailed discussion of PLS path modelling is provided, highlighting the key components required to develop a PLS path model. A path model is essentially a diagram that visually represents the hypotheses and relationships between variables, which can then be tested using the Structural Equation Modelling (SEM) technique [111]. A PLS path model can be understood in terms of two main components: the structural model (also known as the inner model) and the measurement model (also referred to as the outer model) [112]. Together, these two models form a complete PLS path model, with the structural model illustrating the relationships between latent variables, and the measurement model linking the latent variables to their respective observed indicators.

The structural model consists of constructs and the relationships between them. Constructs are variables that are not directly measured but are instead represented as circles or ovals within the model. The relationships between these constructs are represented as arrows in the path model, indicating the directional influence or effect between the latent variables. This structure helps in visualizing and testing the theoretical framework by establishing how the constructs are

interconnected and how they influence each other.

The measurement models consist of indicator variables and the relationships between these variables and the constructs. Indicator variables are directly measurable proxy variables, also known as items or manifest variables, and they represent raw data. These are depicted as rectangles in the path model. The relationships between the constructs in the structural model and the indicator variables in the measurement model show as arrows, indicating the connection between the latent constructs and their corresponding indicators. Additionally, it's important to note that there are two types of measurement models based on latent (unobservable) variables: reflective and formative, each with distinct characteristics in terms of how the indicators relate to the constructs. If the latent variables (i.e., the constructs) in the model explain other constructs, this is referred to as the measurement model of exogenous latent variables. In this case, the exogenous variables are those that influence other constructs within the model but are not explained by other constructs.

Conversely, if the constructs are explained by other constructs in the model, this is called the measurement model of endogenous latent variables. Endogenous constructs are those that are dependent on other variables within the model. To develop a PLS path model, a theoretical foundation is essential, with theory referring to a set of related hypotheses. Hypotheses are individual propositions that are systematically developed and logically connected, and they can be empirically tested to explain and predict outcomes. In the context of a PLS path model, two types of theory are necessary: structural theory and measurement theory. Structural theory deals with the relationships between the latent variables (constructs) in the model, while measurement theory focuses on how those latent variables are measured and how the indicators (observed variables) relate to them. These theories form the basis for

building and validating the path model in PLS-SEM.

3.5.2 Types of models in SEM

Structural Equation Modeling (SEM) consists of two interrelated models: the measurement model and the structural model [108]. The measurement model, also known as Confirmatory Factor Analysis (CFA), defines the constructs (latent variables) used in the model and assigns observed variables to each construct. The structural model, alternatively known as regression or path analysis, specifies the hypothetical relationships among the latent variables [108]. In this study, CFA was employed to assess the validity of the measurement model. CFA was chosen over Exploratory Factor Analysis (EFA) due to the explicit definition of constructs and their corresponding observed variables, based on the research framework and existing literature. It is crucial to clarify that a latent variable represents a theoretical construct that cannot be directly observed. Latent variables can take either an exogenous form (independent variable) or an endogenous form (dependent variable) in the model. The first step in evaluating a model is referred to as the measurement model, which utilizes Confirmatory Factor Analysis (CFA) to assess both the reliability (measured using Cronbach's α and composite reliability) and validity (measured through convergent and discriminant validity) of the model. The measurement, or outer model, employs factor analysis to determine the extent to which observed variables are aligned with their underlying construct [109].

Although the theoretical model outlined in Chapter 3 is built on well-established and widely accepted research streams in the field of information systems, which may not necessitate further measurement reassessment, it is still recommended to conduct CFA to confirm the

relationships between the observed variables and the latent factors. The criteria for fitting the measurement model.

3.6 Data Analysis

3.6.1 Measurement of reliability

In the assessment of the measurement model, the first criterion is to evaluate the internal consistency of the observed variables/items. Specifically, item reliability measures the proportion of variance in an item that can be explained by its underlying latent variable. A widely accepted rule is that the absolute correlation, represented by the standardized outer loadings, should explain at least 50% of the variance of the latent construct [109]. However, it is generally recommended that the factor loadings should exceed 0.7 (which is approximately the square root of 0.5) and values no less than 0.4 are also considered acceptable [117].

Based on the PLS measurement analysis, Table 5.22 presents the absolute correlations (i.e., factor loadings) between the constructs and their respective measuring items. The loadings are above the minimum threshold of 0.4, with values ranging from 0.58 to 0.95, thereby meeting the requirements for psychometric reliability testing [113]. This confirms that the items used in the model are adequately measuring the intended constructs and satisfies the reliability standards for the measurement model [113].

$$\lambda_{ij} = \frac{\text{Cov}(X_i, \eta_j)}{\sqrt{\text{Var}(X_i) \cdot \text{Var}(\eta_j)}} \quad (1)$$

Where X_i represents observed item and η_j denotes latent construct.

3.6.2 Measurement of reliability (Construct-level)

The construct-level reliability ensures that the items assigned to the same construct show strong correlations with each other. While the individual item reliability was already adequate, it is still recommended to evaluate the reliability of the construct as measured by the collective set of items within the same construct. In this study, construct-level reliability was assessed using Cronbach's α and composite reliability. Cronbach's α measures the unidimensionality of a multi-item scale, reflecting its internal consistency, while composite reliability (similar to factor reliability) gauges how well the construct is measured by its assigned items [114]. Table 5.26 shows that Cronbach's α exceeded the required value of 0.6 [115], and composite reliability was higher than the recommended threshold of 0.7 [116]. These results confirm that the constructs are reliably measured by their respective items, meeting the necessary reliability standards for the measurement model.

$$\alpha = \frac{N \cdot \bar{c}}{\bar{v} + (N - 1) \cdot \bar{c}} \quad (2)$$

Where N represents number of items, $\bar{c}$ is average covariance between items, and $\bar{v}$ denotes average variance of items.

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum \epsilon_i} \quad (3)$$

Where:

- λ_i : Standardized loading of item i.
- ϵ_i : Error variance of item iii, calculated as $1 - \lambda_i^2$.

3.6.3 Measurement of validity (Convergent validity):

Validity refers to the extent to which a set of measurement items accurately reflects the underlying theoretical concept that they are intended to represent [117]. Specifically, convergent validity explains that the correlation between responses gathered through different methods should represent the same construct. In other words, a set of items should reflect a single underlying construct, which can be confirmed through their unidimensionality [113].

In this study, convergent validity was assessed using the widely accepted Average Variance Extracted (AVE) method [113], [117]. AVE, initially proposed by Fornell and Larcker, measures the amount of variance a construct captures from its associated measurement items in comparison to the variance due to measurement error. Table 5.23 shows that the AVE for each construct exceeded the required threshold of 0.5 (50%) [107], indicating that each construct is capable of explaining more than half of the variance in its measuring items on average. This confirms the convergent validity of the constructs in the study, ensuring that the items collectively represent the intended underlying concepts.

$$AVE = \frac{\sum \lambda_i^2}{n} \quad (4)$$

Where:

λ_i : Standardized loading of item i.

n: Number of items.

3.6.4 Measurement of validity (Discriminant validity):

Discriminant validity is a complementary concept to convergent validity, emphasizing that two conceptually distinct constructs should show significant differences. In other words, the

measurement items for each construct should not be unidimensional [113]. In this study, discriminant validity at the construct level was assessed using the Fornell and Larcker criterion, while at the item level, the Chin criterion was applied [109]. According to the Fornell and Larcker criterion, the square root of the AVE for each construct should be greater than its correlation with any other construct (i.e., the inter-construct correlation). Table 5.23 shows that no inter-construct correlation exceeded the square root of the AVE, thus meeting the discriminant validity criterion. At the item level, Chin suggested examining the cross-loadings within the factor loadings [109]. Table 5.22 confirms that the factor loading of each measuring item within a construct was higher than all its cross-loadings, both row-wise and column-wise. In fact, all cross-loadings were lower than the recommended threshold of 0.4 [117], further validating the discriminant validity of the model at the item level.

$$\sqrt{AVE_{ii}} > r_{ij} \quad \forall j \neq i \quad (5)$$

Where:

- AVE ii: AVE for construct i.
- r_{ij} : Correlation between constructs i and j.

3.6.5 Assess Collinearity Issues

In assessing the structural model, it is important to examine collinearity issues, as high collinearity between exogenous constructs can bias the path coefficients, leading to unreliable results. To ensure the accuracy of the structural model, the collinearity among predictor constructs is assessed individually for each subpart of the model. Similar to the evaluation in the formative measurement model, Variance Inflation Factor (VIF) values are used to detect collinearity. If the VIF values exceed 5 for any exogenous construct, it

indicates significant collinearity at a critical level. In such cases, the problematic constructs should either be removed, merged into a single construct, or restructured as higher-order constructs to address collinearity issues within the structural model [103], [118].

$$VIF = \frac{1}{1 - R^2} \quad (6)$$

Where R^2 is the coefficient of determination for the predictor.

3.6.6 Assess Significance and Relevance of Relationships

To evaluate the significance and relevance of the hypothesized relationships in the structural model, path coefficients are used. These coefficients, which range from -1 to $+1$, indicate the strength and direction of the relationships between constructs. Path coefficients close to $+1$ typically represent strong positive relationships and are statistically significant, while those closer to -1 usually indicate weak or insignificant relationships. After assessing the statistical significance of relationships, it is essential to evaluate their relevance. Even if the path coefficients are significant, their small size could imply a weak practical impact. Therefore, evaluating the relevance of significant relationships is crucial for interpreting the results. This ensures that the relationships are not only statistically significant but also meaningful in terms of their practical implications for the research [103].

$$t = \frac{\text{Path Coefficient}}{\text{Standard Error}} \quad (7)$$

3.6.7 Assess Coefficient of Determination (R^2 Value)

One of the most commonly used criteria for evaluating the structural model is the coefficient of determination (R^2 value), which measures the model's predictive power [119]. This metric reflects the combined impact of all exogenous constructs on the endogenous

constructs, providing a measure of in-sample predictive accuracy [120]. The R^2 value ranges from 0 to 1, with higher values indicating greater predictive accuracy. However, the acceptable R^2 value varies depending on the complexity of the model and the research field. As a result, it is difficult to establish a universal rule for what constitutes an acceptable R^2 value. For instance, in marketing research, R^2 values of 0.75, 0.50, and 0.25 for endogenous constructs are considered substantial, moderate, and weak, respectively [110], [113].

$$R^2 = \frac{\text{Explained Variance}}{\text{Total Variance}} \quad (8)$$

3.6.8 Assess Effect Size f^2

In addition to examining R^2 values, changes in R^2 , known as effect size (f^2), can also be explored as part of the model evaluation. The f^2 effect size evaluation technique, first introduced by Cohen [122], measures the substantive impact of each independent construct on the dependent construct. This approach assesses how removing a specific exogenous construct affects the endogenous constructs, thereby revealing the influence of the omitted variable on the model. The f^2 effect size is gaining increasing support from reviewers and journal editors for its inclusion in structural model assessments [103]. Therefore, it has been considered in this study alongside the R^2 evaluation. The guidelines for interpreting the f^2 effect size are as follows: values of 0.35, 0.15, and 0.02 indicate large, medium, and small effects of the exogenous construct, respectively [122]. An effect size is considered negligible if the value is below 0.02. This method enhances the understanding of how each predictor construct contributes to the overall model, providing a clearer picture of its structural significance.

$$f^2 = \frac{R^2_{\text{included}} - R^2_{\text{excluded}}}{1 - R^2_{\text{included}}} \quad (9)$$

3.6.9 Normed Fit Index (NFI)

The Normed Fit Index (NFI) is one of the earliest model fit measures introduced in SEM literature by Bentler and Bonett [123]. It calculates the χ^2 value of the proposed model and compares it with the χ^2 value of the null model, which serves as a benchmark. The NFI is computed as 1 minus the ratio of the χ^2 value of the proposed model to that of the null model. The NFI yields values ranging from 0 to 1, with higher values indicating better fit. Generally, an NFI value above 0.90 is considered acceptable, though this threshold can be difficult to achieve. In practice, NFI values closer to 1 indicate a better fit of the model to the data, reflecting a stronger alignment with the proposed relationships in the structural model [124].

$$\text{NFI} = 1 - \frac{\chi_{\text{proposed}}^2}{\chi_{\text{null}}^2} \quad (10)$$

3.6.10 Standardized Root Mean Square Residual (SRMR)

The Standardized Root Mean Square Residual (SRMR) is a fit measure that calculates the difference between the observed correlation and the model-implied correlation, a concept initially introduced for CB-SEM. However, Henseler [125] evaluated the use of SRMR in the PLS-SEM context and recommended it as a goodness-of-fit measure for PLS-SEM as well, helping to prevent model misspecification. SRMR is an absolute measure of model fit, meaning that a value of zero represents a perfect fit. For CB-SEM, a value less than 0.08 is typically considered to indicate a good fit. However, this threshold is often considered too low for PLS-SEM. Therefore, a more conservative threshold value of 0.10 is generally accepted as indicating a good model fit in PLS-SEM [126]. This threshold provides a balance between model precision and practical application.

$$SRMR = \sqrt{\frac{\sum(\text{Observed Correlation} - \text{Predicted Correlation})^2}{n}} \quad (11)$$

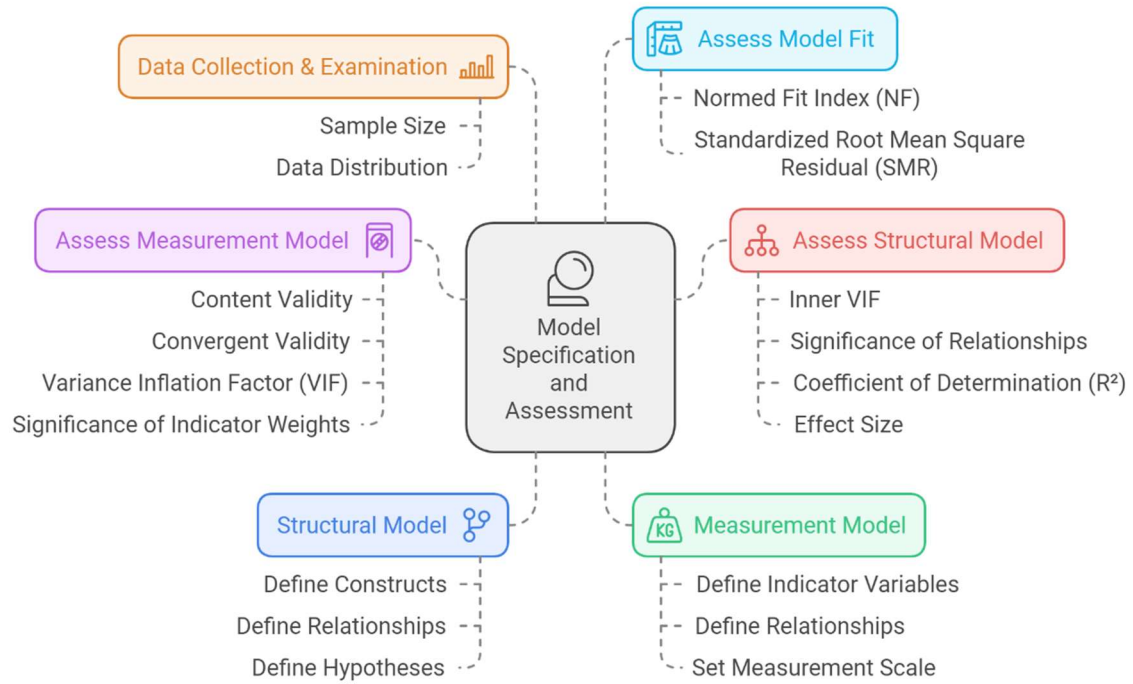


Figure 8: SMART PLS Procedures

3.7 STRUCTUAL EQUATION MODELING

To validate or reject the formulated hypotheses regarding the relationship between the implementation of Digital Twins in an organization and its project success, Structural Equation Modeling (SEM) will be employed. SEM is a comprehensive data analysis technique used to understand the interactions between constructs [90]. It integrates several analytical approaches, including confirmatory factor analysis, multiple regression analysis, and path analysis, to systematically examine how constructs are related and assess the strength and significance of these relationships. This technique is particularly useful for testing complex theoretical models and is widely applied in various research fields to

explore causal relationships and validate hypotheses. The measurement model is used for confirmatory factor analysis, assessing how well latent constructs are represented by their corresponding observed indicators. The structural model, on the other hand, is employed for multiple regression analysis and path analysis to explore and model the relationships between latent variables and final outcomes [127]. SEM requires two sets of variables: latent constructs and observable indicators. Latent constructs are groups of variables that cannot be directly measured; in this study, these constructs include the Digital Twin functions and the project success dimensions. Observable indicators, as shown in Tables 5 and 6, are variables that can be directly observed and measured, serving as proxies for the latent constructs in the model.

3.8 DATA COLLECTION AND ANALYSIS

The current study will employ Google Forms as the primary tool for the design and distribution of the questionnaire. This platform was chosen for its accessibility, ease of use, and its capability to reach a wide demographic, which is crucial for obtaining a representative sample. To ensure the integrity of the collected data, a predetermined threshold for an adequate number of responses will be set, based on statistical power analysis. Upon reaching this threshold, indicating sufficient sample size, we will proceed with the analysis phase. Utilizing the robust analytical capabilities of IBM's SPSS software, we will conduct a series of descriptive statistical analyses. These analyses will provide a comprehensive overview of the data's central tendencies, dispersion, and distributional properties, offering initial insights into the patterns and trends within the responses. Prior to the application of more complex modeling techniques, the questionnaire will undergo a rigorous pretesting phase. This phase will encompass normality tests to assess the

distribution of the data, reliability tests to evaluate the internal consistency of the scales used, and validity tests to ensure that the measures accurately capture the constructs they are intended to represent. These preliminary tests are essential to establish the soundness of the questionnaire for subsequent analyses.

Once the questionnaire's robustness is confirmed, the study will employ Structural Equation Modeling (SEM) to examine the relationships between the observed variables and the underlying latent constructs. SEM is chosen for its ability to test complex causal relationships and to handle multiple regression equations simultaneously, making it particularly suitable for the research questions posed in this study. The application of SEM will be directed toward testing the hypothesized model derived from the theoretical framework, thus providing a deeper understanding of the dynamics at play.

3.9 SURVEY DESIGN AND DISTRIBUTION

This research will employ a survey questionnaire as a pivotal instrument for data collection. The structure of the survey is meticulously designed to facilitate the respondents in providing reflective and insightful responses based on their personal experiences pertaining to the subject matter. To ensure that the collected data yields meaningful analysis, the questions will be carefully selected and formulated with the objective of eliciting specific, measurable, and analyzable replies. This will enable the research to draw valid and reliable conclusions from the statistical examination of the responses. Upon completion, the draft of the survey will undergo a rigorous validation process. This process involves presenting the survey questions to a panel of experts who are well-versed in the relevant subject area. Their role will be to critically assess the survey's content for clarity, relevance, and comprehensiveness. They will provide constructive feedback and recommendations, which

will be instrumental in refining the questionnaire to better capture the nuances of the research domain. Subsequent chapters of the thesis will delve into the intricacies of the questionnaire development. These chapters will articulate the rationale behind the distribution strategies employed, the methodologies adopted for efficient data gathering, and the analytical techniques used to parse through the data. Emphasis will be placed on the methodologies for ensuring the reliability and validity of the data, as well as the statistical methods used for analysis.

This will encompass a thorough exposition of the data handling procedures, from the initial collection stages through to the final stages of analysis, thereby ensuring a transparent and replicable research process.

3.9 VALIDATION OF DIGITAL TWIN IMPLEMENTATION FRAMEWORK

In order to determine the relevance and application of a Digital Twin implementation framework for construction projects in Saudi Arabia in terms of improving project success, it is imperative that this framework be validated. To guarantee a thorough evaluation of the framework in light of actual construction advances, this validation process makes use of a qualitative technique. Key experts from two particular case studies covering significant construction projects in Saudi Arabia were interviewed in-depth. The respondents, who were selected based on their leadership positions and areas of expertise, were asked to offer strategic insights into how Digital Twin technology was being used in their individual projects. These two case studies were carefully chosen to reflect various project dynamics, scales, and levels of complexity in the construction sector, guaranteeing a varied examination of the difficulties and best practices in the application of digital twins.

The purpose of the interviews was to examine how the characteristics of Digital Twin technology specifically, functional capabilities and security (interoperability, predictive analytics, and security and privacy), data handling and integration (real-time data integration and historical data storage), communication and interaction (two-way communication), and representation and modelling (virtual representation and simulation and analysis) affect project success. Project management and leadership, project efficiency, stakeholder satisfaction, and business success are the components of a successful project. The qualitative information cleaned from these conversations shed light on the complexities, difficulties, and practical implementation of these crucial elements in actual environments. By providing context and depth to the findings and guaranteeing a comprehensive grasp of the framework's applicability in the construction sector, this qualitative dimension enhances the validation process.

The research assesses how well the framework captures the crucial components required for the success of Digital Twin implementations in Saudi Arabian construction projects by compiling and analyzing the findings from these interviews. The components of the framework can be improved thanks to this validation process, which guarantees that they accurately reflect both strategic aims and the operational realities encountered by experts in the field. In order to determine the relevance and application of a Digital Twin implementation framework for construction projects in Saudi Arabia in terms of improving project success, it is imperative that this framework be validated. To guarantee a thorough evaluation of the framework in light of actual construction advances, this validation process makes use of a qualitative technique. Key experts from two particular case studies covering significant construction projects in Saudi Arabia were interviewed in-depth. The respondents, who were selected based on their leadership positions and areas of expertise,

were asked to offer strategic insights into how Digital Twin technology was being used in their individual projects. These two case studies were carefully chosen to reflect various project dynamics, scales, and levels of complexity in the construction sector, guaranteeing a varied examination of the difficulties and best practices in the application of digital twins.

CHAPTER 4

RESULTS AND DISSCUTION

Overview

This chapter presents a detailed analysis of the data collected and the results obtained from the study. The analysis was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM), which involved two key steps: assessment of the measurement model and assessment of the structural model. The measurement model evaluated the reliability and validity of the constructs, while the structural model tested the hypothesized relationships between the variables to assess their significance.

The study focused on understanding the impact of Digital Twin functions on project success. The target population included project managers and engineers in the engineering industry. Data was collected via a structured questionnaire distributed through email, aimed at maximizing the response rate from relevant professionals. The questionnaire consisted of three sections: general information about the respondent, Digital Twin-related information, and details about the latest project the respondent participated in. By targeting professionals actively involved in engineering projects, the survey aimed to gather reliable insights into the influence of Digital Twin technology on project outcomes. This targeted approach ensured the data collected was both relevant and actionable, aligning with the study's objectives to evaluate the practical applications of Digital Twins in real-world scenarios [128].

4.1. DATA COLLECTION

The population for this survey focused on organizations within the engineering sector, particularly those involved in construction and related fields, in Saudi Arabia. The survey targeted professionals within this sector, aiming to capture insights from a representative sample. A total of 255 responses were collected, which is considered sufficient for analysis using a Structural Equation Model (SEM). This response rate provides a solid foundation for the reliability and validity of the model and its findings. The questionnaire was sent through personal emails to engineers working in construction organizations, with a focus on project managers in the construction field. The questionnaire was divided into three sections. The first section asked general information about the respondents' backgrounds, their organizations, and general questions regarding the presence of digital twin technology and the employees involved. Unlike the random population, the targeted survey did not include questions about the type of industry or sector, as it focused exclusively on construction organizations in the private sector. At the end of this section, there was a transitional question asking respondents, “Does your organization use digital twin technology or any department that performs similar functions?” with “Yes” or “No” options. Those who replied “No” were automatically directed to the last (third) section, where they were asked to respond to questions on a five-point Likert scale regarding project performance success measures based on the last project they were involved in.

Fifteen project success measures were shown in Table 3.2, adopted from [129], which had been validated by experts and researchers in project management with over 20 years of experience in the field. Respondents who selected “Yes” to the transitional question were automatically guided to the next section, which contained detailed questions about the use

of digital twin technology in their organizations. The core of this section asked respondents to rate the effectiveness of eight digital twin functions on a 5-point Likert scale, as shown in Table 3.1. The list was filtered and recommended by digital twin experts and researchers in the field, each with more than 20 years of experience.

The Likert scale for project success measures was arranged 1 to 5, where 1= strongly disagree, 2=disagree, 3=neutral, 4= agree and 5= strongly agree. While for digital twin functions the 1 to 5 Likert made as 1= Not effective at all, 2= Not effective, 3= of some effectiveness, 4= considerably effective and 5 = Very effective.

4.2 General Information

4.2.1 Years of Experience in The Local Market of Saudi Arabia

The largest group of respondents has 4-6 years of experience (26.7%), indicating that a significant portion of the sample is relatively early in their careers in Saudi Arabia. About 36.9% of respondents have more than 10 years of experience, representing a seasoned group of professionals who could provide more in-depth insights into long-term industry trends. Overall, the sample has a balanced representation of different experience levels, making it a comprehensive dataset for understanding a range of perspectives within the industry.

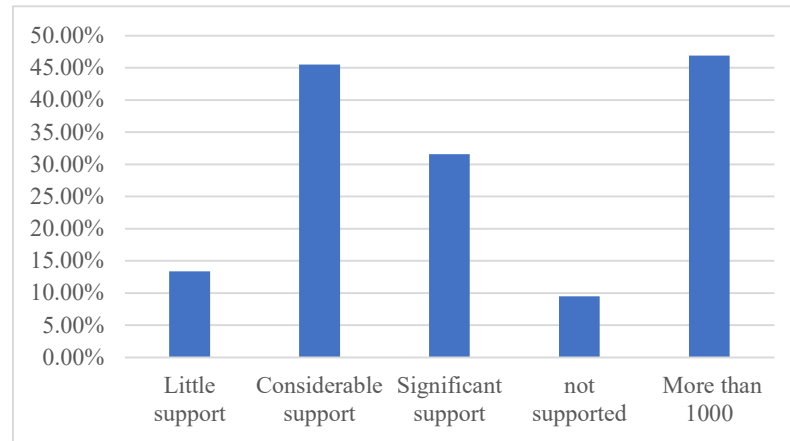


Figure 9: Years of experience of respondents

4.2.2 Occupation or Position

Nearly half of the respondents (49%) are engineers, emphasizing the technical nature of the participant group. The remaining 51% is a mix of managers, consultants, and other positions, indicating that there is also representation from leadership, advisory, and various roles, which helps provide a more well-rounded understanding of organizational structures and practices.

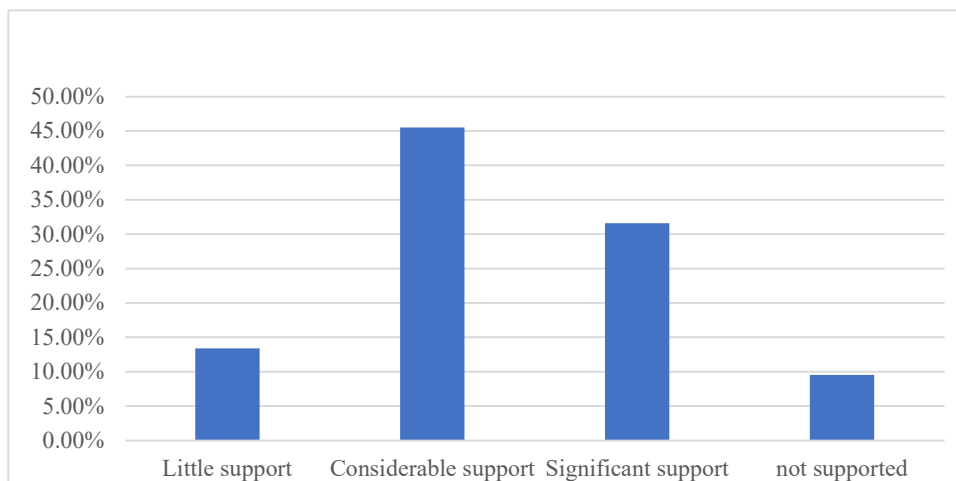


Figure 10: Occupation or Position

4.2.3 Company's Sector

The largest proportion of respondents are from the construction sector (47.5%), highlighting the dominant role of construction in the context of Digital Twins and industry developments in Saudi Arabia. The diversity of respondents from other sectors such as oil & gas, structural design, and management consulting indicates that Digital Twins technology is being utilized across a broad range of industries, offering insights into how this technology can be adapted to different contexts.

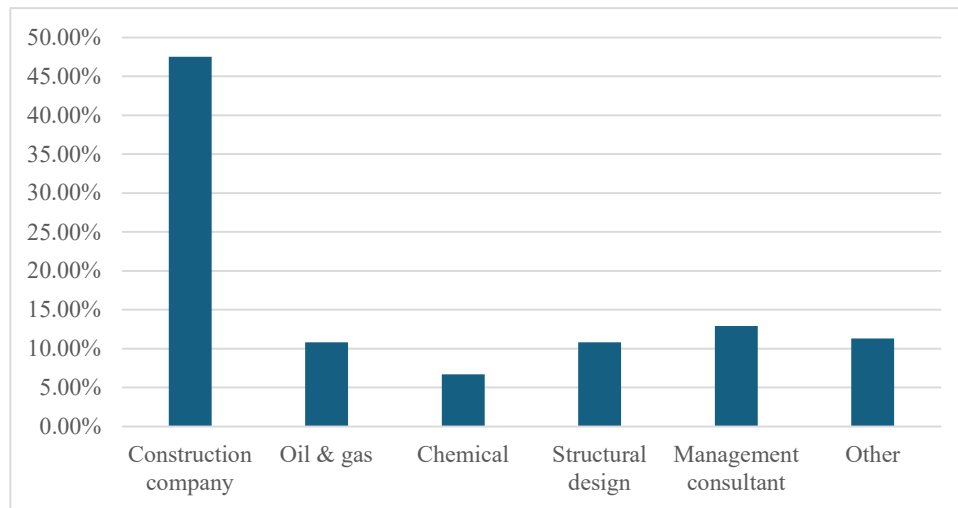


Figure 11: company's sector

4.2.4 Educational Level

The majority of respondents hold bachelor's and master's degrees, with Master's being the highest at 34.9%. This distribution suggests that the workforce engaging with Digital Twins technology is highly educated, with nearly 70% holding at least a bachelor's degree. The presence of PhD holders (13.7%) reflects the involvement of advanced academic professionals in the industry, which could influence innovation and research in the field.

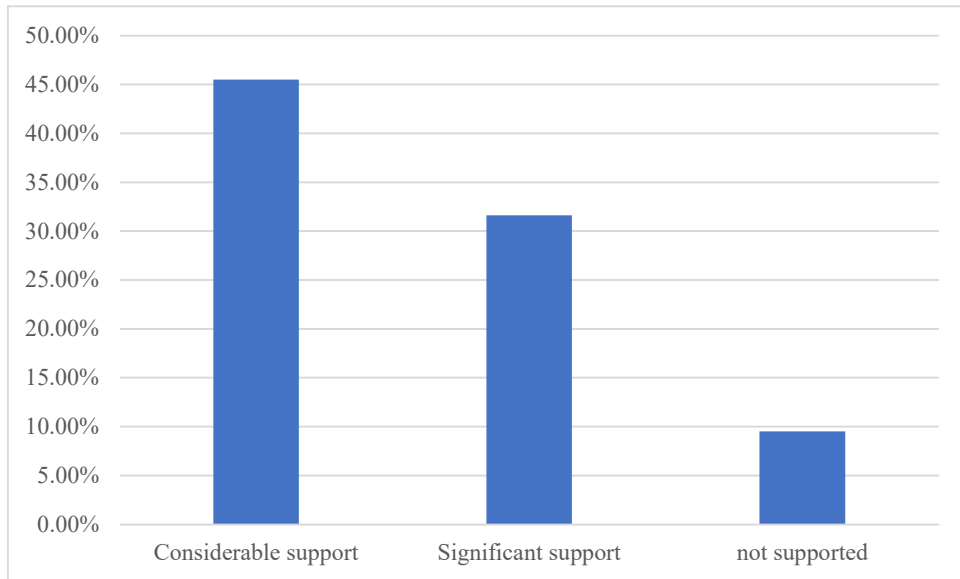


Figure 12: Educational level

4.2.5 Educational Background

The majority of respondents have an engineering background (58.4%), reflecting the technical nature of the industry and the importance of engineering skills in the adoption and implementation of Digital Twins. A smaller but notable group with a business administration background (14.5%) shows that management and operational perspectives are also part of the workforce. The Other category (27.1%) indicates that professionals from various other fields are involved in the application of Digital Twins, underscoring the interdisciplinary nature of the technology.

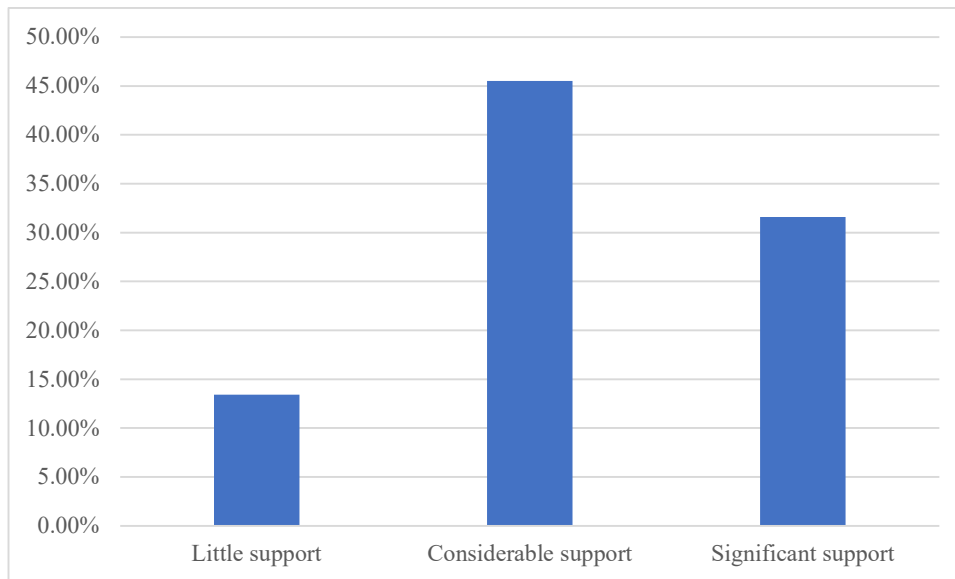


Figure 13: Educational background

4.2.6 Number of Employees in the Organization

A significant proportion of respondents (46.9%) come from large organizations with more than 1000 employees, indicating that Digital Twins technology is being applied in large-scale operations. The presence of respondents from smaller organizations (9.4% from organizations with fewer than 50 employees) suggests that Digital Twins are also relevant in more agile or specialized firms. This distribution showcases that Digital Twins technology is relevant to both large enterprises and smaller companies, each potentially applying the technology in different ways.

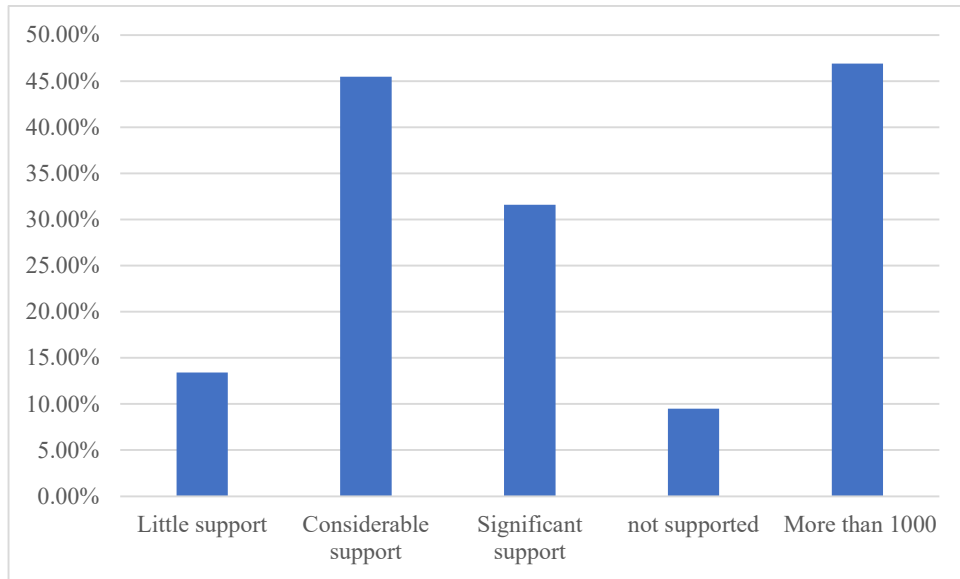


Figure 14: Number of Employees in the Organization

4.2.7 Existence of Digital Twin

A combined 66.2% of respondents have implemented Digital Twins for 3 years or more, indicating that the technology has gained considerable traction in many organizations. Only 13.8% of respondents are in their first year of implementing Digital Twins, suggesting that adoption is still ongoing but more mature in certain industries. The nearly even split between organizations with 3 to 5 years and more than 5 years of experience with Digital Twins indicates that a significant portion of companies have already established the technology as part of their regular operations.

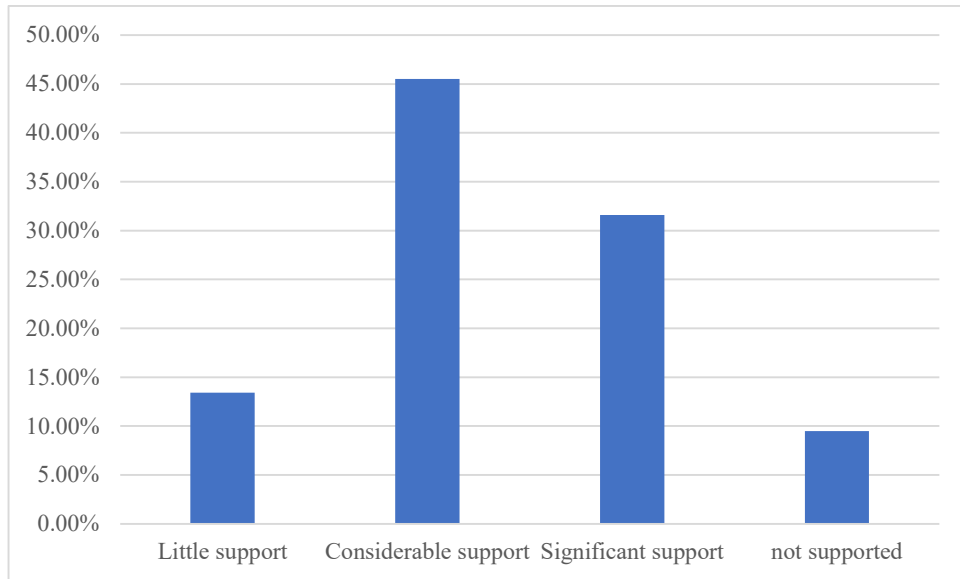


Figure 15: How Long Has This Digital Twin Been in Existence

4.2.8 Support of Digital Twin Technology

A large proportion of respondents (45.5% considerable support and 31.6% significant support) indicates that Digital Twins technology is widely supported within organizations, showing strong internal backing for its use and expansion. Only 9.5% of respondents reported that Digital Twins are not supported, which suggests that most organizations recognize the importance of this technology in their operations. The 13.4% indicating little support may represent organizations that are either in the early stages of adoption or have not yet seen the full potential of the technology.

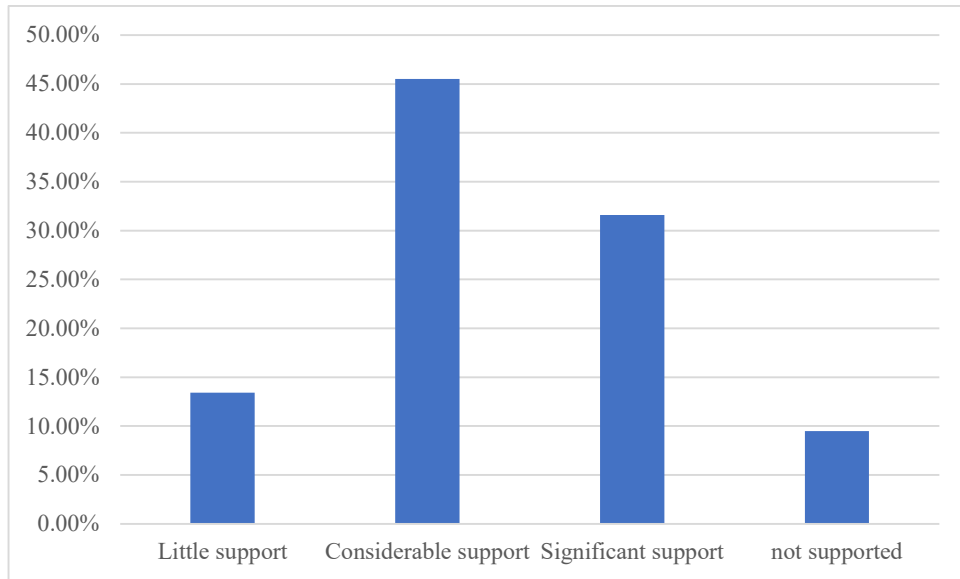


Figure 16: Digital Twin Technology Support

4.3 Model Measurement

Confirmatory Factor Analysis (CFA) was computed using SmartPLS to test the measurement models. As part of confirmatory factor analysis, factor loadings were assessed for each item. The assessment of the criteria starts with evaluation of the factor loadings which is followed by establishing the construct reliability and construct validity (convergent and discriminant).

4.3.1 Factor Loadings

Factor loading refers to the "the extent to which each of the items in the correlation matrix correlates with the given principal component. Factor loadings can range from -1.0 to +1.0, with higher absolute values indicating a higher correlation of the item with the underlying factor" [130]. None of the items in the study had factor loading less than the recommended value of 0.5 [111]. Hence, no items were further removed. Factor loadings are presented in table 8.

Table 8: Factor loadings

Factors	Factor loadings
2WAY <- Comm	1.000
BusSuc <- Success	1.000
C&IF <- Stakeholder	0.923
CM&E <- Project Eff	0.848
Clisat <- Stakeholder	0.900
EnSus <- Project Eff	0.824
HDS <- Data	0.943
INT <- Functional Cap	0.917
Missing <- Project Eff	0.874
PA <- Functional Cap	0.934
PM&L <- Leadership	1.000
QAC <- Project Eff	0.822
RA <- Project Eff	0.825
RTDI <- Data	0.940
S&A <- presentation	0.975
S&H <- Project Eff	0.886
S&P <- Functional Cap	0.917
SDM <- Project Eff	0.821
STAKENG <- Stakeholder	0.890
STM <- Project Eff	0.865
T&I <- Project Eff	0.863
TM <- Project Eff	0.792
VR <- presentation	0.974

The factor loadings table presents a detailed analysis of the relationships between observed variables and their corresponding latent constructs, indicating the reliability and validity of the measurement model. All factor loadings exceed the minimum threshold of 0.7, confirming their strong contribution to the respective constructs, with many loadings surpassing 0.9, signifying an exceptionally robust alignment. The Communication construct is perfectly represented by the Two-Way Communication (2WAY) variable, which exhibits a factor loading of 1.000, indicating that it fully captures the construct's variance. Similarly, Business Success (BusSuc) and Project Management and Leadership (PM&L) also show perfect loadings, highlighting their sole and complete representation of the Success and

Leadership constructs, respectively. For Stakeholder Satisfaction, the items Communication and Information Flow (C&IF), Client Satisfaction (Clisat), and Stakeholder Engagement (STAKENG) demonstrate high loadings (0.923, 0.900, and 0.890, respectively). These values indicate a strong alignment with the construct, with C&IF slightly leading as the most impactful variable. In the Project Efficiency construct, several items contribute significantly, including Change Management & Efficiency (CM&E, 0.848), Safety and Health (S&H, 0.886), and Environmental Sustainability (EnSus, 0.824). The strong performance of these variables emphasizes their critical role in driving project efficiency. In the Data Handling and Integration construct, both Historical Data Storage (HDS) and Real-Time Data Integration (RTDI) exhibit extremely high loadings (0.943 and 0.940, respectively), confirming their pivotal importance in managing data for construction projects. Similarly, the Functional Capabilities and Security construct is well-represented by Predictive Analytics (PA, 0.934), Interoperability (INT, 0.917), and Security and Privacy (S&P, 0.917), with PA emerging as the strongest contributor.

Finally, the Representation and Modelling construct showcases exceptional alignment with Simulation & Analysis (S&A, 0.975) and Virtual Representation (VR, 0.974). These values underscore the critical role of visualization and modelling tools in enhancing project performance. In summary, the factor loadings table confirms the strength of the measurement model, with all variables demonstrating substantial contributions to their respective constructs. This reinforces the validity of the model in capturing the relationships between Digital Twin characteristics and project success, providing a strong foundation for the study's findings.

4.3.2 Indicator Multicollinearity

Variance Inflation Factor (VIF) statistic is utilized to assess multicollinearity in the indicators [107]. Multicollinearity is not a serious issue if the value for VIF is below 5. Table 4.2 presents the VIF values for the indicators in the study and reveals that VIF for each of the indicators is below the recommended threshold [111].

Table 9: Multicollinearity Statistics (VIF) for indicators

Indicators	VIF
Comm -> Leadership	3.093
Comm -> Project Eff	3.093
Comm -> Stakeholder	3.093
Comm -> Success	3.093
Data -> Leadership	4.166
Data -> Project Eff	4.166
Data -> Stakeholder	4.166
Data -> Success	4.166
Functional Cap -> Leadership	3.565
Functional Cap -> Project Eff	3.565
Functional Cap -> Stakeholder	3.565
Functional Cap -> Success	3.565
presentation -> Leadership	3.604
presentation -> Project Eff	3.604
presentation -> Stakeholder	3.604
presentation -> Success	3.604

The Variance Inflation Factor (VIF) values provided in the table assess multicollinearity among the independent variables in the model. Multicollinearity occurs when predictor variables are highly correlated, which can distort the results of regression analysis. In this case, all VIF values are below the commonly accepted threshold of 5, indicating that multicollinearity is not a critical issue for this model. The Communication (Comm) construct has a consistent VIF value of 3.093 across its relationships with the dependent variables, suggesting moderate correlation with other predictors but no severe multicollinearity. Similarly, the Data Handling and Integration (Data) construct shows

slightly higher VIF values of 4.166, reflecting a stronger relationship with the dependent variables but still within acceptable limits. The Functional Capabilities and Security construct has a VIF of 3.565, while Representation and Modelling (Presentation) shows a VIF of 3.604. These values are slightly higher than Communication but remain well below the threshold, confirming that these predictors do not introduce significant collinearity issues. Overall, the VIF values demonstrate that the independent variables are sufficiently distinct to allow reliable interpretation of the structural model's path coefficients, ensuring that the results accurately capture the relationships between Digital Twin characteristics and project success.

4.3.3 Reliability Analysis

Reliability refers to the consistency and stability of a measuring instrument, emphasizing the ability to produce consistent results when repeated over time. The fundamental aspect of reliability is repeatability if the instrument is used multiple times, it should yield similar results each time [131]. The two most commonly employed methods for assessing reliability are Cronbach's Alpha and Composite Reliability (CR). In this study, the reliability results for Cronbach's Alpha ranged from 0.728 to 0.899, while Composite Reliability statistics ranged from 0.816 to 0.923. Both of these measures exceed the required threshold of 0.70, indicating that the constructs in the model exhibit strong reliability [110]. The reliability statistics for each test were calculated using the equations outlined in Equations 1, 2, and 3 [103]. This confirms that the model's constructs are reliably measured, ensuring the robustness of the findings.

$$\text{Cronbach's } \alpha = \frac{Nc}{v + (N - 1)c} \quad (4.1)$$

Where N is the number of items, $\bar{c}$ is the average inter-term covariance among the terms and v

is the average variance.

$$AVE = \frac{\sum \lambda_i^2}{N} \quad (4.2)$$

Where λ is the factor loading and n is the number of variables in the construct

$$CR = \frac{N^2 \cdot \bar{\lambda}^2}{N^2 \cdot \bar{\lambda}^2 + (1 - \bar{\lambda}^2) \cdot N} \quad (4.3)$$

Where λ is the factor loading and σ is the measurement error or residual covariance.

All constructs in the study have Cronbach's α values greater than 0.7, indicating high reliability and consistency in the measurement of their respective variables. Additionally, the Average Variance Extracted (AVE) and Composite Reliability (CR) values, which exceed 0.5, demonstrate the strong validity and reliability of the constructs in the model. These results, as shown in Table 4.1, confirm that all three parameters—reliability, validity, and construct measurement quality meet the recommended thresholds [132]. The values presented further validate the robustness of the measurement model, ensuring the accurate and consistent representation of the constructs in the study.

Table 10: The Average Variance Extracted (AVE), Composite Reliability (CR) and Cronbach's Alpha α Tests

SN	Label	Construct	AVE	CR	α
1	DT1	Representation	0.95	0.94	0.94
2	DT2	Functional Cap	0.85	0.91	0.91
3	DT3	Data handling	0.89	0.87	0.87
4	DT4	Communication	0.98	0.89	0.89
5	PS1	Project efficiency	0.71	0.95	0.95
6	PS2	Stakeholders	0.82	0.89	0.89
7	PS3	Project management	0.90	0.91	0.88
8	PS4	Business Success	0.99	0.89	0.74

The table presents the reliability and validity metrics for the measurement model, highlighting key indicators such as Average Variance Extracted (AVE), Composite

Reliability (CR), and Cronbach's Alpha (α). These metrics confirm the robustness of the constructs and their alignment with the underlying theoretical framework.

Cronbach's Alpha (α) values for all constructs are above the minimum threshold of 0.7, indicating strong internal consistency across the items. Constructs such as Project Efficiency (0.95) and Representation (0.94) demonstrate particularly high reliability, signifying that their respective items are highly correlated and measure the construct effectively. Other constructs, including Functional Capabilities (0.91) and Stakeholders (0.89), also exhibit strong reliability, further strengthening the consistency of the measurement model.

The Composite Reliability (CR) values, which assess the reliability of the construct by considering the loadings of its indicators, all exceed the threshold of 0.7, confirming robust construct reliability. For instance, Representation (0.94) and Project Efficiency (0.95) stand out with exceptional CR values, indicating that these constructs are well-measured by their items. Even constructs with relatively lower CR values, such as Business Success (0.89), remain well within acceptable limits, showcasing strong reliability.

Convergent Validity, as assessed by AVE, demonstrates that all constructs explain more than half of the variance in their respective indicators, with AVE values exceeding the recommended 0.5 threshold. Representation (0.95) and Business Success (0.99) achieve particularly high AVE values, reflecting the substantial contribution of their items to the construct. While constructs like Stakeholders (0.82) and Functional Capabilities (0.85) have comparatively lower AVE values, they still exceed the required threshold, indicating that their indicators adequately converge to represent the underlying constructs. In summary, the reliability and validity metrics confirm that the measurement model is robust and well-suited for analyzing the relationships within the structural model. High Cronbach's Alpha,

Composite Reliability, and AVE values collectively establish the strength of the constructs and their indicators, ensuring the model's suitability for drawing meaningful conclusions. As validity and reliability tests are within acceptable limits it means that the variables fit within each construct, hence, the SEM model that was first built in chapter 3 is calculated.

4.3.4 Construct Validity

Statistically using PIS-SEM, construct validity is established when there is convergent validity and discriminant validity.

4.3.4.1 Convergent Validity

Convergent validity refers to the extent to which multiple measures of the same concept are consistent with each other. In other words, if two or more measures are valid, they should demonstrate a high degree of correlation. This concept suggests that different measurement methods for the same construct should yield similar results [133]. In this study, convergent validity was assessed using the Average Variance Extracted (AVE). When the AVE value is greater than or equal to 0.50, it indicates that the items are converging to measure the underlying construct, thus confirming convergent validity [107]. Based on the AVE statistics, the results show that all constructs, except for DC and TI, have AVE values slightly below 0.5. However, the Composite Reliability (CR) values for all constructs exceed the acceptable threshold of 0.7, which suggests that convergent validity remains intact despite the slightly lower AVE values for DC and TI. Table 4.3 presents the AVE values for each construct, further supporting that convergent validity is not an issue in this study.

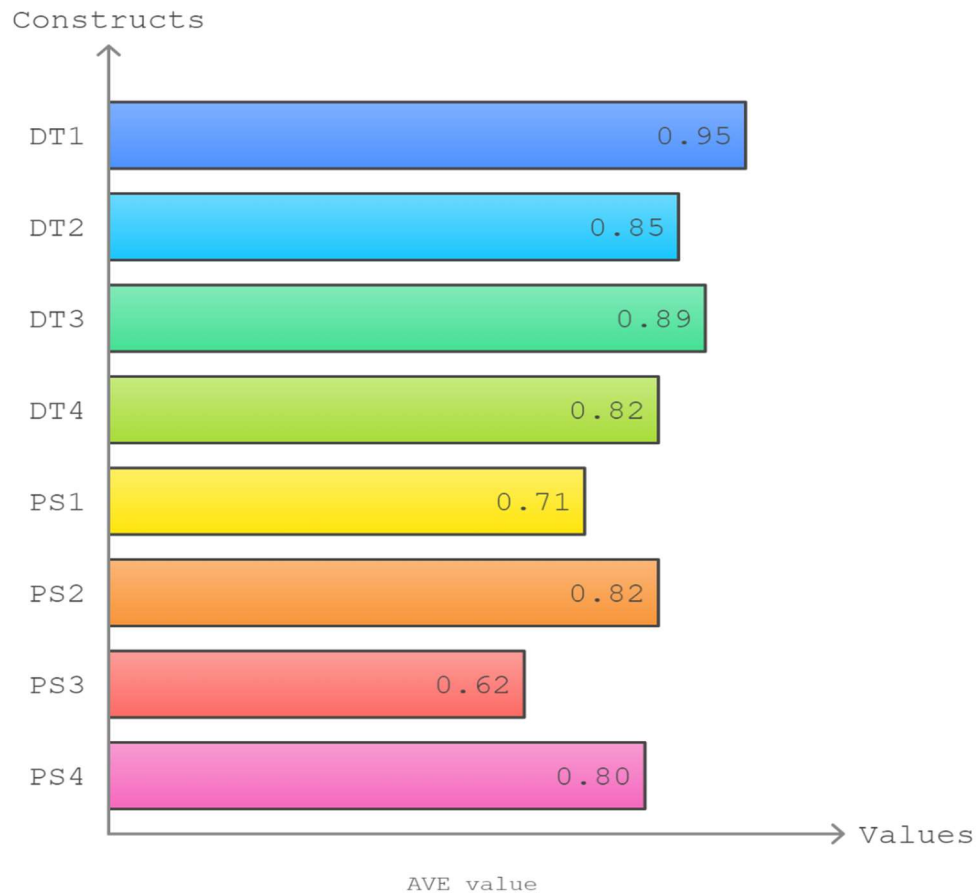


Figure 17: AVE value

4.3.4.2 Discriminant Validity

Discriminant validity refers to the extent to which measures of different constructs are distinct from each other. The principle behind this concept is that if two constructs are truly separate, then their respective measures should not show high correlation with one another. In other words, valid measures of distinct constructs should be conceptually different and not overlap significantly. This ensures that each construct in a model represents a unique aspect of the phenomenon being studied and prevents constructs from being incorrectly assumed to be related when they are not [133].

4.3.4.2.1 Fornell and Larcker Criterion

According to the Fornell and Larcker criterion, discriminant validity is confirmed when the square root of the Average Variance Extracted (AVE) for a construct exceeds its correlation with all other constructs. In this study, the square root of AVE for each construct (denoted in bold and italics) was found to be greater than its correlation with other constructs, as shown in Table 11. This result provides strong evidence for the establishment of discriminant validity, ensuring that the constructs in the model are sufficiently distinct from one another [107].

Table 11: Fornell and Larcker test

	AVE	$\sqrt{AVE}$	Comm	Data	Functional Cap	Leadership	Project Eff	Stakeholder	Success	presentation
Comm	0.98	0.99	<i>1.00</i>							
Data	0.89	0.94	0.78	<i>1.00</i>						
Functional Cap	0.85	0.92	0.76	0.79	<i>1.00</i>					
Leadership	0.97	0.98	0.60	0.66	0.65	<i>1.00</i>				
Project Eff	0.71	0.84	0.66	0.73	0.77	0.83	<i>1.00</i>			
Stakeholder	0.82	0.90	0.67	0.71	0.74	0.80	0.84	<i>1.00</i>		
Success	0.98	0.99	0.55	0.63	0.65	0.75	0.85	0.84	<i>1.00</i>	
presentation	0.95	0.97	0.73	0.81	0.79	0.69	0.75	0.70	0.65	<i>1.00</i>

The table presents the Average Variance Extracted (AVE) values and the square root of AVE along with inter-construct correlations for the model, which are key indicators of convergent and discriminant validity. Square root of AVE, displayed diagonally, represents the degree to which each construct explains the variance of its own indicators, while the off-diagonal elements represent correlations between constructs. The Square root of AVE values are

consistently higher than the inter-construct correlations for each construct, confirming discriminant validity based on the Fornell-Larcker criterion. For example, Communication has a higher value than its correlations with other constructs, such as Data (0.78) and Leadership (0.60), ensuring that Communication is distinct from these constructs.

4.3.4.2.2 Heterotrait-Monotrait Ratio (HTMT)

HTMT (Heterotrait-Monotrait Ratio) is used to assess discriminant validity based on the estimation of correlations between constructs. The Hill ratio is utilized to determine whether discriminant validity is established, with various thresholds debated in the literature. Mihos suggested a threshold of 0.85 or less, while other sources recommend a more liberal threshold of 0.9 or less [134], [135]. The HTMT results in this study, as shown in Table 12, indicate that the HTMT ratio for all constructs is below the required threshold of 0.9, thus confirming the establishment of discriminant validity for the model. This ensures that the constructs are sufficiently distinct from each other.

Table 12: Heterotrait-Monotrait Ratio

	Heterotrait-monotrait ratio (HTMT)
Data <-> Comm	0.842
Functional Cap <-> Comm	0.800
Functional Cap <-> Data	0.888
Leadership <-> Comm	0.600
Leadership <-> Data	0.706
Leadership <-> Functional Cap	0.681
Project Eff <-> Comm	0.678
Project Eff <-> Data	0.799
Project Eff <-> Functional Cap	0.826
Project Eff <-> Leadership	0.847
Stakeholder <-> Comm	0.711
Stakeholder <-> Data	0.817
Stakeholder <-> Functional Cap	0.820
Stakeholder <-> Leadership	0.853
Stakeholder <-> Project Eff	0.978

Success <-> Comm	0.555
Success <-> Data	0.681
Success <-> Functional Cap	0.684
Success <-> Leadership	0.751
Success <-> Project Eff	0.877
Success <-> Stakeholder	0.892
presentation <-> Comm	0.748
presentation <-> Data	0.896
presentation <-> Functional Cap	0.849
presentation <-> Leadership	0.707
presentation <-> Project Eff	0.785
presentation <-> Stakeholder	0.764
presentation <-> Success	0.671

4.3.5 Goodness of Fit (Model's predictive capabilities)

To evaluate the goodness of fit, the coefficient of determination (R^2) and effect size (f^2) were assessed in this study. The analysis revealed R-squared (R^2) values indicate the proportion of variance in each dependent variable that is explained by the independent variables in the model. These values reflect the predictive power of the structural model for each construct, with higher values suggesting better explanatory strength. The Leadership construct has an R^2 value of 0.52, indicating that 52% of the variance in leadership outcomes is explained by the predictors, which suggests a moderate level of predictive accuracy. Similarly, Stakeholder Satisfaction has an R^2 value of 0.61, demonstrating that 61% of its variance is accounted for by the independent variables, reflecting a strong influence of factors such as communication, data handling, and functional capabilities. Project Efficiency, with an R^2 value of 0.66, shows the highest predictive power among the constructs, indicating that 66% of its variance is explained by the predictors. This emphasizes the critical role of Digital Twin functionalities in enhancing project efficiency. On the other hand, Business Success has an R^2 value of 0.48, meaning that 48% of its variance is explained, which, while lower than other constructs, still reflects a moderate level of explanatory power. Overall, the R^2

values provide evidence of the model's ability to predict outcomes effectively, with constructs such as Project Efficiency and Stakeholder Satisfaction showcasing strong predictive relationships. According to the recommended 0.10 cutoff value [136], this result suggests that the model achieves a substantial level of fit.

Table 13: R-square value

Variables	R-square
Leadership	0.52
Project Eff	0.66
Stakeholder	0.61
Success	0.48

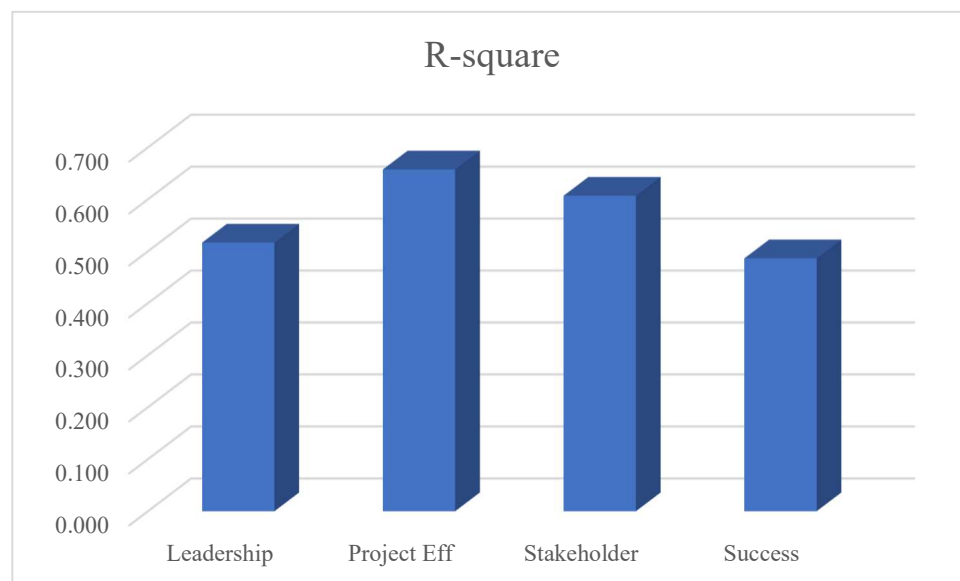


Figure 18: R Square bar chart

According to Hair, it is recommended that *f* effect size shall also be presented. *f* effect size statistic specifies if removal of an independent variable from the model can have a substantial impact on the dependent variable [137]. The analysis results of *f* statistic the effect sizes of the independent variables on the dependent variables, highlighting their relative impact. Functional Capabilities and Representation and Modeling stand out with

higher contributions, particularly to Project Efficiency (0.13, 0.06 respectively) and Stakeholder Satisfaction (0.09, 0.02). These findings emphasize the importance of predictive analytics, interoperability, and visualization in driving project success. While Communication and Data Handling show smaller effect sizes (values of 0.01– 0.04), their consistent influence across constructs like Leadership and Business Success underscores their foundational role. Together, these results validate the contributions of Digital Twin functionalities to project outcomes, particularly in enhancing efficiency and stakeholder engagement. Cohen’s effect size values of 0.02, 0.15, and 0.35 suggest small, medium, and large effects, respectively [122],[113]. The effect size and its significance are presented in table 14. Overall, the statistic indicates that the independent variables have a medium effect showing a medium predictive relevance [111].

Table 14: f-square value

	f-square
Comm -> Leadership	0.02
Comm -> Project Eff	0.04
Comm -> Stakeholder	0.03
Comm -> Success	0.01
Data -> Leadership	0.02
Data -> Project Eff	0.02
Data -> Stakeholder	0.03
Data -> Success	0.02
Functional Cap -> Leadership	0.02
Functional Cap -> Project Eff	0.13
Functional Cap -> Stakeholder	0.09
Functional Cap -> Success	0.06
presentation -> Leadership	0.07
presentation -> Project Eff	0.06
presentation -> Stakeholder	0.02
presentation -> Success	0.04

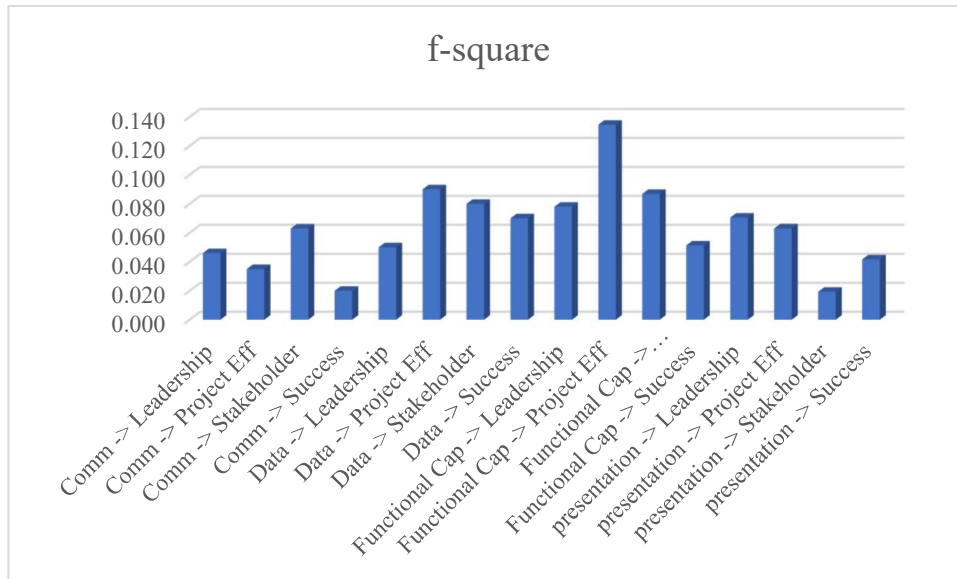


Figure 19: f-square bar chart

Apart from the mentioned statistics, Standardized Root Mean Square Residual (SRMR) can also be used as a measure of fit. A value less than 0.10 or 0.08 is considered a good fit. The value of SRMR in the present study is 0.064 [126].

Table 15: Measure of fit

Fit Indices	Recommended Value	Source	Obtained Value
SRMR	<0.08	Hair et al. Hu	0.04
NFI	>=0.9	Hair et al,	0.90

4.3.6 Path Coefficient Analysis

The impact of various factors on project success in construction projects, especially with the integration of Digital Twins, reveals a clear hierarchy of influence among communication, data handling, functional capabilities, and presentation. Starting with Functional Capabilities, the strong path coefficient of 0.306 indicates that technical expertise and the ability to execute tasks effectively are crucial for success. This is supported by the similarly

high influence of Functional Capabilities on both Project Efficiency (0.405) and Stakeholder Management (0.349), showing that skilled teams not only ensure smooth operations but also build confidence among stakeholders, enhancing overall project management and collaboration. Moreover, Functional Capabilities' effect on Leadership (0.183) reinforces the notion that competent teams provide a solid foundation for strong, decisive leadership, which in turn drives the project toward successful outcomes.

In parallel, Data Handling plays a critical role, with a positive and moderate influence on Success (0.194), indicating that the ability to manage and utilize data effectively enhances decision-making and project tracking. Data Handling's significant impact on Stakeholder Management (0.224) and Leadership (0.180) further highlights the importance of real-time, accurate information in ensuring that stakeholders are kept informed and leaders can make informed, data-driven decisions. Additionally, the influence of Data Handling on Project Efficiency (0.166) illustrates that well-managed data directly supports streamlined operations, contributing to improved project timelines and resource allocation.

Presentation also emerges as a strong driver of success, with a notable path coefficient of 0.278 for Success, showing that how information is conveyed greatly affects project outcomes. A clear and structured presentation of plans and data enables better decision-making, directly influencing Project Efficiency (0.279) and Stakeholder Management (0.165), as stakeholders and team members are more likely to stay aligned and engaged when they are presented with relevant, digestible information. Furthermore, the 0.350 path from Presentation to Leadership underscores the importance of effective communication in shaping leadership capabilities, as leaders who can present their vision and strategies effectively tend to foster better team collaboration and decision-making.

On the other hand, Communication plays a somewhat lesser role in project success. With a slightly negative path coefficient of -0.034 for Success, it suggests that while communication is necessary, it must be structured and purposeful to avoid misalignment or confusion. However, Communication still has a significant positive impact on Stakeholder Management (0.107) and Leadership (0.063), indicating that clear, regular communication helps maintain stakeholder trust and supports leadership in guiding teams through complex projects. Communication's minimal effect on Project Efficiency (0.021) suggests that while it is necessary for coordination, other factors like functional capabilities and data management are more critical in driving operational efficiency.

Together, these findings highlight that while communication, data handling, and presentation all contribute to various aspects of project success, Functional Capabilities consistently outweigh the other factors across multiple dimensions, particularly in influencing leadership, efficiency, stakeholder management, and overall success. This underscores the reality that, in complex construction projects involving advanced technologies like Digital Twins, the skills and expertise of the team are the most decisive factors in determining whether a project will succeed.

Table 16: Path coefficient

Latent variables	Path coefficients
presentation -> Leadership	0.350
presentation -> Project Eff	0.279
presentation -> Stakeholder	0.165
presentation -> Success	0.278
Functional Cap -> Leadership	0.183
Functional Cap -> Project Eff	0.405
Functional Cap -> Stakeholder	0.349
Functional Cap -> Success	0.306
Comm -> Leadership	0.063
Comm -> Project Eff	0.021

Comm -> Stakeholder	0.107
Comm -> Success	-0.034
Data -> Leadership	0.180
Data -> Project Eff	0.166
Data -> Stakeholder	0.224
Data -> Success	0.194

4.3.7 HYPOTHESIS TESTING USING STRUCTURAL EQAUTION MODELING PLS-SEM

To test the hypotheses outlined in Section 3.1.4 of Chapter 3, a model examining the relationship between Digital Twin technology and project success was developed using Structural Equation Modeling (SEM). The SEM model for this population was constructed to address the sixteen hypotheses generated in Chapter 3, Section 3.1.4 using SMART-PLS, following validation of the groupings through convergent validity testing. The PLS-SEM model presented in Figure 4.1 illustrates the path coefficients (arrows indicating relationships between constructs) and factor loadings (arrows between constructs and observed variables). These factor loadings are satisfactory, as all variables have values greater than 0.7, indicating strong relationships between the constructs and their respective observed variables [132]. This demonstrates the model's robustness and the adequacy of the data for hypothesis testing.

Table 17: Hypothesis testing results

Hypothesis	Mean	Std.	T-value	P-value	Decision
presentation -> Leadership	0.348	0.093	3.757	0.000	Supported
presentation -> Project Eff	0.277	0.077	3.603	0.000	Supported
presentation -> Stakeholder	0.162	0.077	2.160	0.031	Supported
presentation -> Success	0.274	0.092	3.004	0.003	Supported

Data -> Leadership	0.180	0.091	1.988	0.047	Supported
Data -> Project Eff	0.167	0.071	2.343	0.019	Supported
Data -> Stakeholder	0.225	0.077	2.903	0.004	Supported
Data -> Success	0.196	0.092	2.099	0.036	Supported
Functional Cap -> Leadership	0.187	0.081	2.260	0.024	Supported
Functional Cap -> Project Eff	0.407	0.069	5.846	0.000	Supported
Functional Cap -> Stakeholder	0.354	0.073	4.801	0.000	Supported
Functional Cap -> Success	0.306	0.090	3.407	0.001	Supported
Comm -> Leadership	0.061	0.082	0.777	0.437	Rejected
Comm -> Project Eff	0.019	0.065	0.318	0.750	Rejected
Comm -> Stakeholder	0.105	0.070	1.525	0.127	Rejected
Comm -> Success	-0.033	0.088	0.384	0.701	Rejected

4.3.7.1 Hypothesis outcomes discussion

1.The structural model reflects the hypothesized relationships outlined in the research framework. It is assessed based on R^2 values and the significance of the paths between constructs.

2. The goodness of fit for the model is assessed based on the strength of the structural paths, which is quantified by the R^2 value of the dependent variable. To establish predictive capability, the R^2 value must meet or exceed the threshold of 0.1 [136], [138]. As illustrated in Figure 4.1, all R^2 values exceed the threshold of 0.1, affirming the model's predictive validity. Furthermore, the model fit was assessed using the SRMR metric, which yielded a value of 0.039. Since this is well below the accepted limit of 0.10, it indicates that the model demonstrates a good fit with the data [111].

3.To further assess the goodness of fit, the hypotheses were tested to determine the significance of the relationships between constructs. As indicated in Table 4, twelve out of sixteen hypotheses were supported, while four were not. This suggests that the model successfully explains most of the proposed relationships but that some hypotheses were not supported by the data.

H1: Digital Twins in Representation and Modelling positively impact Project Management and Leadership.

Digital twins in modelling and representation greatly improve project management and leadership, according to the analysis ($t = 3.757$, $p = 0.000$). This implies that leaders may see whole projects in depth using digital technologies like 3D modelling and virtual simulations. Clear insights into the project's status, possible obstacles, and significant milestones are provided by this representation. In actuality, this implies that project managers are able to anticipate problems that would have been hard to see with conventional techniques, like conflicts in building designs or resource allocation delays. Digital twins' real-time feedback also enables leaders to act instantly on data-driven decisions, increasing responsiveness and strategic alignment with project objectives.

H2: Digital Twins in Representation and Modelling positively impact Project Efficiency.

According to the results, project efficiency is greatly increased by digital twins ($t = 3.603$, $p = 0.000$). In building projects, where misunderstandings and delays can result in higher expenses and longer schedules, efficiency is essential. Digital Twins facilitate improved planning and execution by allowing project teams to model different situations. Teams can use simulations, for example, to plan logistics to reduce downtime, optimize workflow sequences, and more efficiently deploy resources. Furthermore, being able to virtually see the planning and construction stages of a project aids in averting expensive mistakes before

they happen. These skills are crucial for preserving productivity and cutting waste in real-world projects, such major infrastructure upgrades, which results in significant cost savings and improved project performance.

H3: Digital Twins in Representation and Modelling positively impact Stakeholder Management & Satisfaction.

Digital twins have a considerable impact on stakeholder management and satisfaction, according to the data ($t = 2.160$, $p = 0.031$). In large projects, accurate reporting, openness, and clear communication are frequently necessary for stakeholder satisfaction. Stakeholders can visualize project progress and comprehend the effects of changes in real time with the help of digital twins, which offer an interactive and dynamic platform. Misunderstandings and misalignments, which are frequent in intricate projects with multiple stakeholders, are decreased by this improved communication. For instance, stakeholders are more likely to feel included and secure in the decision-making process when they can view a virtual depiction of the present and future states of a project. This proactive approach to stakeholder engagement fosters support and trust, both of which are essential for a project's successful completion.

H4: Digital Twins in Representation and Modelling positively impact Business Success.

Digital twins significantly improve business success, according to the study ($t = 3.004$, $p = 0.003$). In construction projects, fulfilling project deadlines, producing high-quality outputs, and attaining cost efficiency are frequently critical to business success. By avoiding delays, cutting down on rework, and allocating resources as efficiently as possible, the use of digital twins for precise project planning and visualization results in improved financial performance. Additionally, the project's reputation and client satisfaction—two important components of long-term economic success—are enhanced by the increased transparency

and stakeholder interaction made possible by digital twins. Digital twins are essential for ensuring that project outputs are in line with corporate goals in high-value projects like public infrastructure or commercial real estate.

H5: Development of Digital Twin-based Data Handling and Integration positively impacts Project Management and Leadership.

The results demonstrate that Project Management and Leadership are highly impacted by Data Handling and Integration with Digital Twins ($t = 1.988$, $p = 0.047$). In complicated projects, having fast and reliable data access is essential for effective leadership. Data from several sources, including sensors, equipment, and project reports, may be seamlessly integrated into a single platform thanks to digital twins. By giving project managers, a thorough and up-to-date picture of the state of their projects, this integration enables them to spot problems early and take preventative action. This translates into improved coordination and more efficient decision-making in practice by enabling project managers to be more sensitive to circumstances on the ground. For example, real-time data might notify the leadership to deploy more resources or modify deadlines if a crucial project component is running behind schedule.

H6: Development of Digital Twin-based Data Handling and Integration positively impacts Project Efficiency.

Project efficiency and data handling and integration were found to be significantly positively correlated by the study ($t = 2.343$, $p = 0.019$). It can be difficult to manage and utilize massive amounts of data in the construction industry. By combining historical and real-time data, digital twins give project managers the ability to track key performance indicators (KPIs) across time and spot inefficiencies. Managers can plan maintenance proactively, for instance, by examining real-time equipment performance data, preventing unplanned

malfunctions that might cause delays. By taking a proactive approach to data management, resources and time are used more effectively, which eventually improves project productivity and results.

H7: Development of Digital Twin-based Data Handling and Integration positively impacts Stakeholder Management & Satisfaction.

The results show that Stakeholder Management & Satisfaction are highly impacted by Data Handling and Integration using Digital Twins ($t = 2.903$, $p = 0.004$). Access to correct information and openness are two of the main demands of stakeholders. Real-time data sharing is made easier by digital twins, which provide stakeholders with the most recent information on project status, risks, and possible problems. Stakeholders feel more engaged in the direction and choices of the project because of the collaborative atmosphere this accessibility promotes. Project stakeholders in a large-scale urban development, for instance, can get real-time information on cost projections and environmental implications, boosting their trust in the project's management.

H8: Development of Digital Twin-based Data Handling and Integration positively impacts Business Success.

Data integration and handling have a major impact on business success, according to the results ($t = 2.099$, $p = 0.036$). Business success in construction projects is determined by the ability to provide value to stakeholders and clients in addition to financial rewards. Digital Twins help project teams learn from the past, see trends, and implement best practices by enhancing data integration. Better alignment with business objectives, reduced risks, and improved project quality are the results of this ongoing learning and development. For example, project teams can attain more accurate project planning, which improves financial results and customer satisfaction, by leveraging previous data to fine-tune cost estimates and

timetables.

H13: Digital Twins' support for Functional Capabilities and Security positively impacts Project Management and Leadership.

The results demonstrated that Project Management and Leadership are significantly improved by Functional Capabilities and Security in Digital Twins ($t = 2.260$, $p = 0.024$). Leaders may better manage complicated tasks and risks in large-scale projects by leveraging advanced technology capabilities like interoperability and predictive analytics. Predictive analytics, for example, can give leaders information about possible project delays or cost overruns, enabling them to take pre-emptive measures. Furthermore, knowing that project data is secure and safeguarded when robust security measures are in place allows executives to concentrate on strategic decisions.

H14: Digital Twins' support for Functional Capabilities and Security positively impacts Project Efficiency.

The findings showed that security and functional capabilities greatly increase project efficiency ($t = 5.846$, $p = 0.000$). A crucial part of functional skills, predictive analytics enables project teams to anticipate and reduce risks while maximizing time and resources. Predictive analytics, for instance, can assist project teams prevent unscheduled downtime by predicting when particular equipment will require maintenance. Furthermore, enabling interoperability among various digital systems facilitates smooth data transfer and team communication, cutting down on redundancies and enhancing project productivity overall.

H15: Digital Twins' support for Functional Capabilities and Security positively impacts Stakeholder Management & Satisfaction.

According to the study, Stakeholder Management & Satisfaction are strongly impacted by

Functional Capabilities and Security ($t = 4.801, p = 0.000$). Stakeholder trust in the project rises when they are given the assurance that project data is safe and that sophisticated analytics are being used to make wise decisions. For example, having strong security procedures and the capacity to forecast project results greatly boosts stakeholders' trust and satisfaction in large-scale building projects where they are worried about data breaches or inadequate risk management.

H16: Digital Twins' support for Functional Capabilities and Security positively impacts Business Success.

The results demonstrated a substantial impact of Digital Twin Security and Functional Capabilities on Business Success ($t = 3.407, p = 0.001$). Project teams may maximize returns on investment, save expenses, and predict market trends with the use of functional capabilities like predictive analytics. Strong security measures also guard against cyberattacks and data breaches, which can have detrimental effects on one's reputation and finances. For example, keeping strong security helps prevent expensive breaches and legal problems in projects containing sensitive client data or intellectual property, safeguarding the project's profitability and reputation.

H9: The significance of Digital Twins in Communication and Interaction has a positive impact on Project Management and Leadership.

According to the statistical findings, there was no discernible effect of the importance of digital twins in communication and interaction on project management and leadership ($t = 0.777, p = 0.437$).

Although it is frequently regarded as an essential component of leadership, communication may have a more indirect effect in the context of digital twins. For digital twins to give

project managers real-time information, data visualization and automated updates are fundamental. This implies that a large portion of decision-making in settings enabled by digital twins may be influenced more by the precision and analysis of data than by conventional routes of communication. Instead, than depending on regular written or spoken reports, leaders might employ Digital Twins as tools to back their decisions. Because the emphasis may be more on the interpretation of digital insights than on overt interactive contact, the two-way communication made possible by digital twins may not necessarily result in improved leadership.

H10: The significance of Digital Twins in Communication and Interaction has a positive impact on Project Efficiency.

The findings showed that digital twin interaction and communication have no discernible effect on project efficiency ($t = 0.318$, $p = 0.750$). According to this research, communication by itself could not be a major factor in determining how efficient initiatives using digital twins are. Rather, the technical and operational capabilities offered by Digital Twins, such real-time data integration and predictive analytics, are probably more directly linked to efficiency gains. Project teams' efficiency is increased mostly through data-driven optimizations rather than through interpersonal or interdepartmental contacts when they have access to simulations and real-time insights. In this environment, direct system updates, notifications, and automated processes are likely more impactful on efficiency than traditional forms of communication, explaining why this hypothesis was not supported.

H11: The significance of Digital Twins in Communication and Interaction has a positive

impact on Stakeholder Management & Satisfaction.

Stakeholder management and satisfaction were not significantly impacted by the importance of digital twins in communication and interaction, according to the analysis ($t = 1.525$, $p = 0.127$).

Stakeholder management requires effective communication, but it seems that in the setting of digital twins, stakeholders might appreciate transparency and access to precise project data more than they do the quantity or quality of interactive communication. When stakeholders receive clear data-driven updates, comprehensive project reports, and visualizations instead of frequent communication updates, they are more likely to be happy. Furthermore, stakeholders can anticipate that Digital Twins will provide project insights and data openness without necessitating extensive two-way communication. This research implies that data accessibility and accuracy may have a greater impact on stakeholder satisfaction in Digital Twin enabled initiatives than contact and communication.

H12: The significance of Digital Twins in Communication and Interaction has a positive impact on Business Success.

According to the study, digital twins in interaction and communication had no discernible effect on business success ($t=0.384$, $p=0.701$).

In construction projects, meeting key performance metrics including cost management, on-time delivery, and customer satisfaction is usually the key to business success. While engagement and communication are crucial for project collaboration, the success of projects with digital twins may depend more on technical skills like functional efficiency and predictive analytics. Through cost reduction, mistake reduction, and workflow optimization,

these factors are directly related to business outcomes. Although communication may facilitate cooperation, it may not directly contribute to financial and operational success unless paired with strong technological capabilities and efficient data administration, as indicated by the non-significant link found here.

Therefore, the more urgent demand for operational competence, process integration, and data correctness may overshadow the importance of communication in this situation.

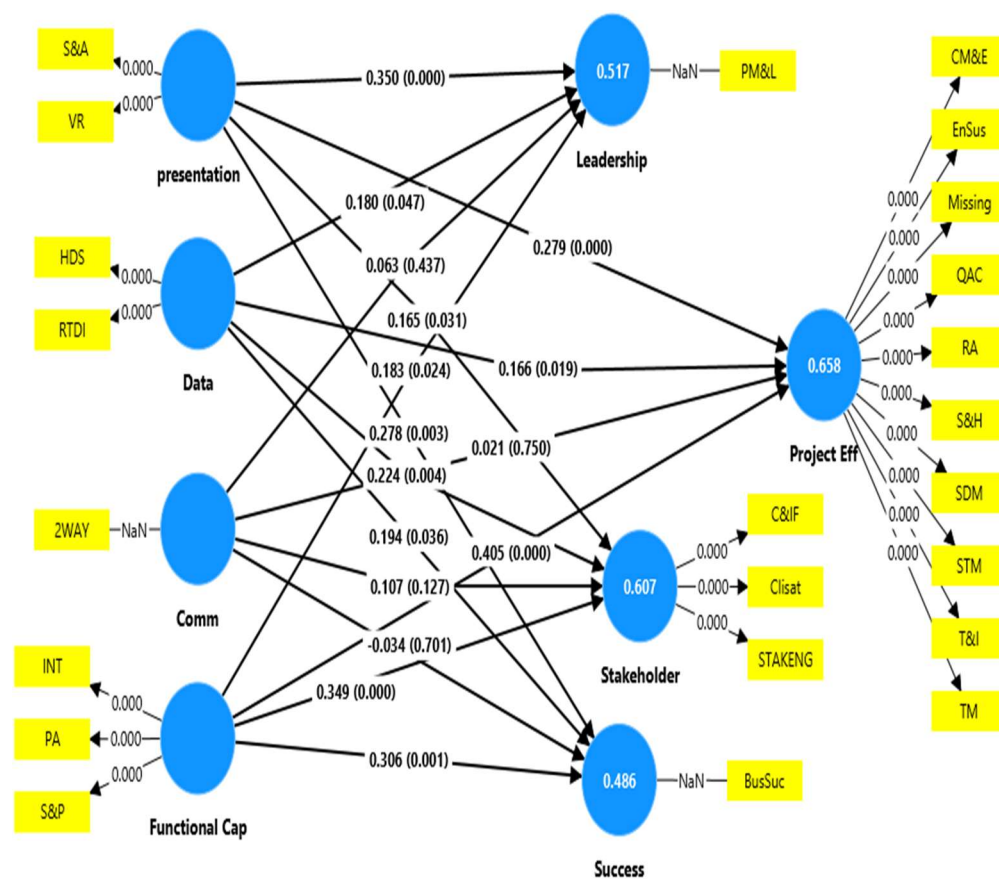


Figure 20: Smart PLS diagram

4.4 VALIDATION OF THE STRUCTURAL EQUATION MODEL

The Process of validation to the research outcomes for implementing Digital Twin technology in construction projects within Saudi Arabia, interviews were conducted as it shows in appendix c with professionals involved in two case studies: Almokhlif Project in Al-Qassim and Alittihad Project in Riyadh. Each case study included two interviewees with significant roles in their respective projects, bringing practical insights and a strategic perspective to the evaluation process and they asked sixteen questions.

This targeted validation approach, engaging directly with top-level project professionals, allowed for a comprehensive assessment of the model's applicability in different contexts. By focusing on real-world experiences from two major projects, the study provided a nuanced, strategic evaluation of the success factors, ensuring that feedback was grounded in practical realities and aligned with high-level project management objectives in the construction sector.

4.4.1 Case Research-1 AL-MOKHLIF Project

Project in Al-Qassim was a strategic initiative aimed at integrating innovative Digital Twin technology within Saudi Arabia's construction sector. This project commenced in December 2023 and was successfully completed in May 2024.

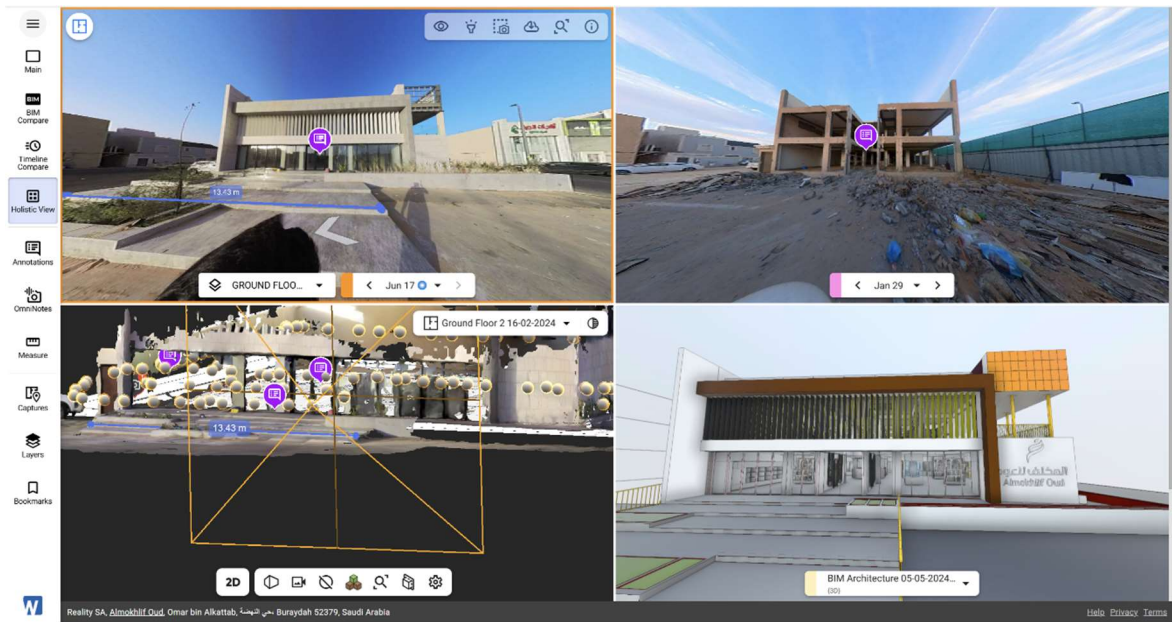


Figure 21: AL-MOKHLIF Project

Director's Response as "Virtual representation and simulation technologies have completely revolutionized how we approach decision-making and leadership within the project. Real-time visualization has empowered us to anticipate problems and address them proactively, leading to more calculated and successful decisions. For instance, we noticed a 15% improvement in project timelines because these tools optimized resources and minimized delays.

Stakeholders have expressed significant satisfaction with the visual capabilities offered by Digital Twin technology, as it aligns well with their expectations and provides clear progress insights. From a business perspective, I firmly believe that this technology gave us a competitive edge in the market, allowing for faster unit sales and better positioning."

"In terms of data handling and integration, real-time data monitoring of KPIs allowed us to make quick and informed decisions. Historical data enabled performance benchmarking and resource optimization, which were critical in staying within the budget. Stakeholders appreciated the transparency and their ability to track progress in real time, which increased

their trust and confidence. Handling data effectively directly contributed to improving our profitability."

"Two-way communication systems were key to better collaboration within the team and stakeholders. Misunderstandings were minimized, and project output increased by 10% due to this enhanced communication. Stakeholders, in particular, valued the transparency and felt more involved, which ensured the project's timely completion."

"The interoperability and predictive analytics capabilities of Digital Twin significantly enhanced overall project efficiency by 20%. These tools allowed us to manage risks proactively and gave stakeholders assurance through strong security and privacy features. This not only built trust but also played a crucial role in achieving financial stability and operational success."

The senior digital engineer who was interviewed also for the same project underlined that "Virtual representation greatly clarified complex plans and significantly enhanced leadership decision-making. These tools helped streamline construction processes and reduced material waste, which in turn minimized costs. Investors and stakeholders found the visual representation particularly helpful in aligning expectations, which enhanced their satisfaction throughout the project."

"Real-time and historical data were indispensable for planning and improving project performance. Real-time updates kept the team flexible and proactive, while historical data enabled us to predict and prevent potential delays. The transparency provided by real-time data comforted stakeholders, boosting their happiness and engagement."

"Implementing two-way communication tools strengthened the project's leadership

capabilities and teamwork. The quicker resolution of issues and reduced downtime led to higher stakeholder satisfaction and increased productivity."

"Predictive analytics and interoperability were essential for tackling project complexities. By anticipating potential risks, predictive analytics empowered us to act before problems materialized, greatly boosting team efficiency. The robust security measures in place also increased stakeholder confidence, ensuring both financial and operational success."

4.4.2 Case Research-2 AL-ITTIHAD Project

This project, situated in Riyadh, stands as a substantial endeavor within the modular housing and construction industry, covering an expansive area of 14,000 square meters, starts on September 2024 and is still ongoing.

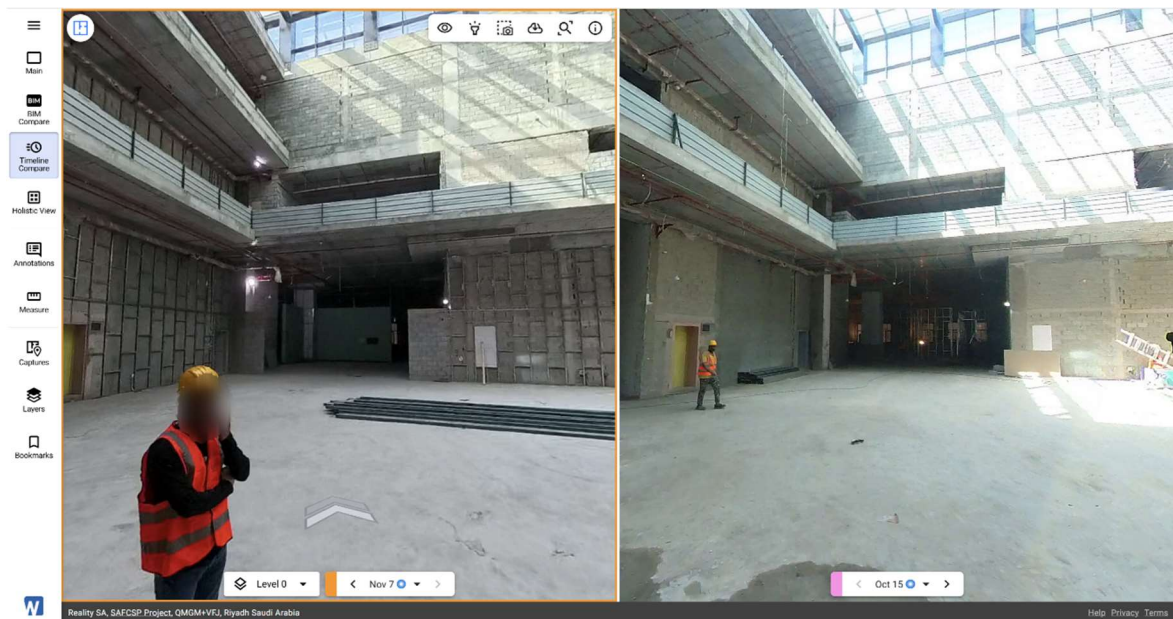


Figure 22: AL-ITTIHAD Project

The digital delivery manager highlighted that "The role of virtual representation was crucial for leadership, enabling us to anticipate bottlenecks and optimize resource allocation. This led to a 12% reduction in material costs. Simulations were key in preventing delays and

maintaining project schedules, and stakeholders greatly appreciated the precise visualizations, which enhanced their satisfaction with the project."

"Real-time and historical data played a significant role in our decision-making. Historical data provided benchmarks for performance comparisons, while real-time updates allowed us to address potential issues proactively, boosting project efficiency by 18%. This transparency-built stakeholder trust and kept the project within budget, contributing to financial performance."

"The implementation of two-way communication technologies was instrumental in managing teams across various locations. This feedback loop cut decision-making delays and enabled quick on-site problem-solving, improving overall efficiency and stakeholder engagement."

"Predictive analytics and interoperability were indispensable for tackling project complexities. The security measures gave stakeholders confidence that their data was safe, while predictive analytics helped us address risks proactively, ensuring both operational and financial success."

The Senior project engineer for the same project emphasized "Simulation and virtual representation were invaluable for decision-making in this large-scale infrastructure project. These tools allowed leadership to view intricate project components clearly, leading to more strategic and efficient decisions. Streamlined processes and adherence to project schedules significantly contributed to the project's financial success."

"Real-time data provided ongoing supervision, and historical data helped us predict and avoid potential obstacles. This increased our overall efficiency by 20%. Stakeholders felt

deeply involved due to the transparency offered by real-time updates, which boosted their confidence in the project."

"The two-way communication system was another critical factor. It facilitated seamless communication between leadership and field teams, ensuring that problems were resolved promptly and effectively. This collaboration reduced delays and enhanced productivity, aiding in the project's timely completion and financial success."

"Predictive analytics and interoperability played an essential role in improving overall project efficiency. Leadership used predictive analytics to foresee and mitigate risks before they materialized. The strong security measures safeguarded sensitive information, strengthening stakeholder trust and contributing to the project's success."

4.4.3 Follow up Comments

- Positive impact of Digital Twin technology, especially in improving efficiency, decision-making, and stakeholder engagement.
- Acknowledged that Digital Twin is still in the early stages in Saudi Arabia, with more potential to be realized.
- Believes that as adoption grows, the technology will become even more effective, improving agility, data-driven decisions, and cost-efficiency.
- Predicts that in the next few years, Digital Twins will revolutionize construction project management in Saudi Arabia.

The hypothesis results and validation responses from the interviews are closely interlinked, showcasing the practical relevance and empirical support for the findings. The quantitative results revealed that Representation and Modeling, Data Handling and Integration, and Functional Capabilities and Security significantly influenced project success metrics like Project Management and Leadership, Project Efficiency, Stakeholder Satisfaction, and Business Success. These insights were corroborated by the validation responses from the interviews, where professionals highlighted how virtual representation improved decision-making, real-time data optimized resource allocation, and predictive analytics enhanced project planning. For instance, interviewees emphasized a 15-20% improvement in efficiency attributed to Digital Twin capabilities, aligning directly with the hypothesis findings. While Communication and Interaction had limited quantitative significance, the interviews revealed its supportive role in fostering collaboration and stakeholder engagement, indicating its indirect impact. This alignment between hypothesis testing and real-world validation underscores the robustness of the proposed framework and its practical application in the construction industry.

Numerous studies have investigated the impact of Digital Twin (DT) technology on project success, supporting the relationships explored in this research. For H1, which examines the role of DT in Representation and Modelling on Project Management and Leadership, researchers such as Qi et al. found that virtual representation and simulation in DT enhance decision-making and managerial efficiency by providing real-time insights into project performance. Similarly, H2, which links DT Representation and Modelling to Project Efficiency, aligns with the findings of Boje et al, who demonstrated that DT-based simulations optimize workflows, reduce resource wastage, and improve overall efficiency in construction. For H3, which examines the impact of DT Representation and Modelling

on Stakeholder Management and Satisfaction, studies such as Lu et al. confirm that interactive DT models foster transparency and collaboration among stakeholders by visualizing project progress and potential risks. H4, which evaluates the influence of DT Representation and Modelling on Business Success, is supported by research from Opoku et al, who found that DT adoption enhances project predictability and reduces cost overruns, leading to greater profitability and client satisfaction.

Moving to H5-H8, which assess DT-based Data Handling and Integration, research supports its positive impact on various project outcomes. For H5, which examines the impact on Project Management and Leadership, studies such as Zhang et al. indicate that real-time data integration enables proactive decision-making, minimizing delays. H6, which relates Data Handling and Integration to Project Efficiency, aligns with research from Wang & Kim, who found that centralized data storage and integration improve workflow coordination, reduce redundancies, and optimize schedules. H7, which explores the link between DT-based Data Handling and Integration and Stakeholder Satisfaction, is reinforced by studies such as García de Soto et al, who highlight that real-time access to historical and real-time data enhances trust among project participants. H8, which focuses on the relationship between Data Handling and Integration and Business Success, is supported by the work of Sawhney et al, who found that efficient data utilization leads to cost savings and improved project forecasting.

Regarding H9-H12, which investigate Communication and Interaction, the results in this study did not support these hypotheses, indicating that two-way communication via DT may not have a significant direct impact on project success. This aligns with the findings of Zheng et al, who noted that while DT enhances information sharing, it does not necessarily translate into improved leadership or stakeholder satisfaction unless complemented by

effective human interaction strategies. Similarly, studies such as Koc and Kumar suggest that project success is influenced more by decision-making frameworks and leadership styles rather than digital communication alone. Finally, H13-H16, which examine the role of Functional Capabilities and Security in project success, are strongly supported by existing literature. For H13, which links DT Functional Capabilities to Project Management and Leadership, studies such as Bilal et al. confirm that predictive analytics and security features improve managerial decision-making and operational control. H14, which examines Project Efficiency, aligns with the findings of Braun et al, who showed that interoperability and automation enhance project workflows. H15, which connects Functional Capabilities with Stakeholder Satisfaction, is supported by the work of Liu et al. who argue that secure and interoperable DT platforms increase stakeholder confidence and trust. Lastly, H16, which links Functional Capabilities to Business Success, is consistent with the research of Opoku et al. who found that DT-enabled security and predictive analytics lead to long-term financial stability and reduced risk exposure in construction projects.

4.5 PRACTICAL IMPLICATIONS

The practical implications of this research on Digital Twin (DT) technology in construction projects are substantial, particularly for project management practices, strategic planning, and technological investment in the construction industry. The findings indicate that Representation and Modelling, Data Handling and Integration, and Functional Capabilities and Security are critical determinants of project success, underscoring the need for construction firms to focus on specific Digital Twin functionalities to enhance their project outcomes. For project managers, the use of Representation and Modelling tools such as virtual 3D models, scenario simulation, and real-time visualization allows for a proactive

approach to risk management, resource allocation, and design optimization. This direct visualization capability supports more accurate planning, as managers can simulate various scenarios to forecast potential issues, reducing the likelihood of on-site disruptions and ultimately lowering project costs. Consequently, firms that invest in comprehensive representation capabilities within their Digital Twin systems can achieve better alignment with project goals, while also enhancing leadership and decision-making efficiency.

Moreover, Data Handling and Integration emerged as an essential factor for real-time decision-making, suggesting that construction companies should prioritize systems that can seamlessly integrate live data from diverse sources, historical project data, and predictive analytics. In practice, this enables teams to monitor ongoing project performance against historical benchmarks, adjust plans based on real-time insights, and quickly respond to unexpected changes in project dynamics. This approach is particularly valuable in large-scale or high-stakes projects, where delays or resource misallocations can have substantial financial repercussions. Real-time data integration further allows for continuous project assessment, ensuring that each phase of the project is informed by accurate, up-to-date information. The practical benefit for construction companies lies in optimizing workflows, streamlining operations, and fostering data-driven project environments that prioritize accuracy and adaptability.

The third significant implication pertains to Functional Capabilities and Security, specifically the need for construction firms to invest in predictive analytics, interoperability, and strong data security measures. Predictive analytics is particularly useful for foreseeing project demands, material requirements, and potential risks, enabling managers to allocate resources with greater precision. Additionally, interoperability among various digital

systems within the project ecosystem ensures that data flows smoothly across platforms, facilitating coordinated efforts among different departments and teams. Robust security protocols further support this interoperability by safeguarding sensitive project data, which is crucial for maintaining stakeholder trust and compliance with data privacy standards. These functionalities not only strengthen operational continuity but also provide firms with a competitive edge by enhancing their capacity to execute complex, data-rich projects securely and efficiently.

In a broader industry context, the results underscore that traditional communication practices may not have as direct an impact on project outcomes in Digital Twin-enabled environments as previously assumed. This finding implies that construction companies should adapt their management practices to leverage automated, data-transparent communication channels that Digital Twins inherently provide. Such a shift can reduce dependency on manual information exchange, streamlining project workflows and allowing teams to focus on actionable insights delivered directly by the Digital Twin system. As a result, firms can reallocate resources traditionally devoted to communication efforts toward strengthening other critical Digital Twin features, such as real-time data integration and predictive capabilities.

Ultimately, these practical implications suggest that construction firms aiming to achieve greater efficiency, cost-effectiveness, and project precision should strategically adopt and prioritize specific Digital Twin functionalities. By doing so, they can drive continuous improvements in project quality, stakeholder satisfaction, and business success, establishing a more resilient and innovative project management framework within the construction industry.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 CONCLUSION

This study set out with a structured objective to understand and enhance the application of Digital Twin (DT) technology in the construction industry. Specifically, the study pursued three core goals: first, to identify and examine the key characteristics of Digital Twins that influence construction projects through a comprehensive research and analysis process; second, to develop a framework for assessing how Digital Twin technology adoption and implementation impacts construction project success; and third, to validate this framework within a real-world construction project case study, thereby testing its effectiveness and applicability. These goals were pursued to bridge the gap in current research regarding the optimal deployment of Digital Twins within the construction industry, especially within the context of the Saudi Arabia construction sector.

Through a mixed-method approach that integrated quantitative and qualitative analysis, the study yielded significant insights into the role of Digital Twins in driving project success. Quantitative analysis of data collected from 255 industry professionals highlighted those three of the four primary Digital Twin characteristics Representation and Modelling, Data Handling and Integration, and Functional Capabilities and Security were strongly linked to positive project outcomes. The findings of this study, based on hypothesis testing and validation interviews, reveal critical insights into the impact of Digital Twin technology on construction project success. The quantitative analysis confirmed 12 out of 16 hypotheses, emphasizing the significant roles of Representation and Modeling, Data Handling and Integration, and Functional Capabilities and Security in driving positive outcomes across

key project success factors.

Representation and Modelling demonstrated a strong influence on Project Management and Leadership ($p = 0.000$) and Project Efficiency ($p = 0.000$), highlighting its capability to enhance visibility and predictability. Validation interviews echoed these results, reporting a 15% improvement in project timelines and enhanced stakeholder alignment through virtual simulations and real-time visualization. In addition, data Handling and Integration was identified as critical for improving Stakeholder Satisfaction ($p = 0.004$) and Business Success ($p = 0.036$). Real-time data tracking and historical data utilization were cited in validation responses as essential for proactive decision-making, contributing to a reported 20% increase in efficiency and strengthened stakeholder trust. For the Functional Capabilities and Security, including predictive analytics and interoperability, showed significant effects on operational stability and financial performance. Validation interviews highlighted these features' ability to mitigate risks, ensure data security, and enhance overall project management capabilities.

Conversely, Communication and Interaction did not exhibit a statistically significant direct impact on project outcomes (e.g., $p = 0.750$ for Project Efficiency). However, validation feedback recognized its indirect role in improving team collaboration and stakeholder engagement, particularly through transparency and quicker issue resolution. These findings collectively underscore the transformative potential of Digital Twin technology in optimizing project execution and success. The integration of validated insights and statistical results provides a robust framework for leveraging Digital Twin functionalities, guiding future strategies in the construction industry.

The implications of this study are substantial both theoretically and practically. The findings contribute to the existing body of knowledge by refining the understanding of how specific Digital Twin features influence project outcomes. Unlike prior studies that broadly advocate for Digital Twin adoption, this research provides empirical evidence specifying the characteristics that should be prioritized for maximum impact. By identifying Representation and Modelling, Data Handling and Integration, and Functional Capabilities and Security as critical factors, this study offers a structured framework that guides construction organizations in leveraging Digital Twins to achieve desired outcomes. Practically, this framework provides actionable insights for construction firms and project managers by identifying the Digital Twin functionalities with the greatest impact on project success metrics. The study suggests that firms should focus on enhancing capabilities in data integration, predictive analytics, and system interoperability to optimize resource allocation, minimize risks, and improve stakeholder satisfaction. For instance, Representation and Modelling allow project teams to visualize complex construction phases, manage risks preemptively, and ensure resource availability. Additionally, the framework encourages firms to leverage predictive analytics for operational forecasting and real-time data handling to maintain accuracy and adaptability, which are crucial in fast-paced, high-stakes construction environments.

Despite the valuable contributions of this study, certain limitations are acknowledged. Firstly, the study's reliance on survey data may introduce a level of subjectivity, as the responses reflect individual perceptions of Digital Twin effectiveness rather than purely objective project outcomes. Although the survey data were supplemented by a real-world case study, the interpretations may still be influenced by personal biases and organizational cultures. Additionally, the geographic focus on Saudi Arabia may affect the generalizability

of the findings, as regional factors such as economic policies, regulatory frameworks, and technological infrastructure may influence the adoption and impact of Digital Twins differently in other regions. Moreover, the research concentrated on four primary Digital Twin characteristics, which, while foundational, may not encompass all relevant aspects influencing Digital Twin efficacy. For example, factors such as infrastructure readiness, organizational digital maturity, and cybersecurity protocols could play critical roles in Digital Twin adoption but were beyond this study's scope. These limitations underscore the need for a broader exploration of contextual and technological variables in future research.

Building on these findings, future research can expand the scope of Digital Twin functionalities by exploring variables beyond those identified in this study. For example, additional studies could investigate the role of digital infrastructure, team training, and cybersecurity in the successful implementation of Digital Twins in construction projects. Comparative studies across regions and industries could also provide insights into how diverse contexts impact the effectiveness of Digital Twin technology, offering a more generalized framework for global application. Furthermore, qualitative research methods, such as in-depth case studies or longitudinal research designs, could provide more nuanced perspectives on the evolving role of Digital Twins throughout a project lifecycle. Longitudinal studies, in particular, could track the long-term impacts of Digital Twin implementation, providing insights into how the technology influences project outcomes from initiation to completion. Additionally, further exploration into the non-significance of Communication and Interaction may reveal contextual factors or specific project conditions where this dimension becomes more impactful, potentially offering new insights into communication dynamics within Digital Twin-enabled environments.

5.2 RECOMMENDATION

Based on the study findings, several recommendations are proposed to maximize the potential of Digital Twin technology in the Saudi Arabian construction industry. First, there is a pressing need to prioritize and enhance key Digital Twin characteristics—particularly Representation and Modelling, Data Handling and Integration, and Functional Capabilities and Security as these were shown to have the most significant positive impact on project success. Efforts should be directed toward developing advanced tools for virtual representation and real-time data handling to improve planning accuracy, stakeholder alignment, and operational efficiency.

Second, initiatives to promote the adoption and integration of Digital Twins across construction projects in Saudi Arabia should be encouraged. This includes fostering collaboration between government bodies, industry leaders, and academic institutions to create policies, standards, and training programs that support Digital Twin implementation.

Third, investments should focus on advancing the Digital Twin infrastructure, including predictive analytics and interoperability features, to address the complexities of large-scale projects. Strengthening data security protocols and privacy measures is equally vital to ensure stakeholder trust and compliance with regulatory standards.

Finally, continued research and innovation are recommended to explore untapped aspects of Digital Twin technology, such as improving two-way communication functionalities, which, while less significant in this study, could contribute to enhanced collaboration in future contexts. By adopting these strategies, the Saudi construction industry can leverage Digital Twins to achieve sustainable, efficient, and high-performing project outcomes aligned with Vision 2030 goals.

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Appendix A

I greatly appreciate your participation in this survey. Your involvement plays a vital role in the advancement of this research.

Section 1

Respondent/Organization Characteristics

1. Years of experience in the local market of Saudi Arabia.

- 1-3 yrs.
- 4-6 yrs.
- 7-9 yrs.
- 10-12 yrs.
- More than 12 yrs.

2. Educational Level

- PhD
- Master
- Bachelor
- Other

3. Educational Background

- Engineering
- Business Administration
- Other

4. What is the total number of employees of your organization

- Less than 50

- 51-100
- 101-500
- 501-1000
- More than 1000

5. What is your organization's sector?

- Private sector
- Public sector

6. At what industry is your organization working?

- IT
- Construction
- Engineering
- Oil & Gas
- Manufacturing
- Other...

Section 2

Identification and assessment of critical success factors:

Kindly evaluate the extent to which each factor contributes to the success of the projects in Saudi Arabia. Indicate your assessment using the following scale:

- Υ 1: not important factor,
- Υ 2: slightly important factor
- Υ 3: important factor
- Υ 4: very important factor
- Υ 5: most important factor

Category	Projects Success Measures	Rating				
1	Project Management and Leadership					
2	Scope Definition and Management					
3	Budget and Cost Control					
4	Schedule and Time Management					
5	Quality Assurance and Control					
6	Risk Management					
7	Stakeholder Engagement					
8	Communication and Information Flow					
9	Regulatory Compliance					
10	Resource Allocation					
11	Safety and Health					
12	Environmental Sustainability					
13	Technology and Innovation					
14	Client Satisfaction					
15	Contractual Arrangements					
16	Market Conditions					
17	Political and Social Factors					
18	Post-Project Evaluation					
19	Stress and Crisis Management					
20	Project Closure (proper completion)					
21	Vendor Management					
22	Change Management					
	If you have any suggestions or recommendations, please provide them in the space below:					

Appendix B
Research Validation
Invitation to Participate in Master's Research Study:

Dear Participant,

We are pleased to invite you to participate in a significant research study entitled '**The Impact of Digital Twin Implementation on Construction Project Success in Saudi Arabia.**' This study is conducted by a student pursuing an M.Sc. in Construction Management at **King Fahd University of Petroleum and Minerals (KFUPM)**. The primary aim of this research is to explore and validate influencing successful implementation of Digital Twin technology in the construction industry within the Saudi Arabian context. Your insights and experiences will be invaluable in enhancing our understanding of how Digital Twin technology can contribute to achieving better project outcomes and overall success in construction projects. Please be assured that your participation in this study will remain confidential, and the information you provide will be used exclusively for academic research purposes. We appreciate your invaluable time and contributions to this important academic endeavours.

Thank you for your participation and support.

If you have any questions, or require further information, please do not hesitate to contact email g202114830@kfupm.edu.sa .

Yours sincerely,

HASSAN ABDELGADIR

M.Sc., Construction Engineering and Management

Dhahran, 31261, Saudi Arabia

Section 1

Interviewee Information

1. Director of Project A
 - Position:
 - Years of Experience:
 - Education:
2. Senior Digital Engineer of Project A
 - Position:
 - Years of Experience:
 - Education:
3. Digital Delivery Manager of Project B
 - Position:
 - Years of Experience:
 - Education:
4. Senior Project Engineer of Project B
 - Position:
 - Years of Experience:
 - Education:

Section 2

Interview questions

The core purpose of this interview is to validate the influencing the successful implementation of Digital Twin technology in construction projects in Saudi Arabia. We will be focusing on case study within the construction sector. Your expertise and insights in this area are highly valued.

As we proceed with the interview, please share your insights on how each digital twin characteristics contributes to the success of construction projects in Saudi Arabia.

1. Representation and Modelling (Virtual Representation & Simulation and Analysis)

- Impact on Project Management and Leadership:
 1. How did the use of virtual representation and simulation tools influence the decision-making processes and leadership strategies in your project?
- Impact on Project Efficiency: 2. To what extent did virtual representation and simulation contribute to improving project efficiency, such as optimizing resources or reducing time delays?
- Impact on Stakeholders Satisfaction: 3. Did the visualization and simulation capabilities of Digital Twin technology improve stakeholder understanding and satisfaction with project progress?
- Impact on Business Success: 4. How did the use of virtual representation and simulation enhance the project's ability to achieve its business goals or overall success?

2. Data Handling and Integration (Real-Time Data Integration & Historical Data Storage)

- Impact on Project Management and Leadership: 5. How did the integration of real-time and historical data impact the project management practices and leadership decisions in your project?
- Impact on Project Efficiency: 6. In what ways did the availability of real-time data and historical records improve project efficiency or performance metrics?
- Impact on Stakeholders Satisfaction: 7. Did the real-time data integration lead to better communication and satisfaction among stakeholders?
- Impact on Business Success: 8. How did the use of historical and real-time data contribute to achieving the project's business success and objectives?

3. Communication and Interaction (Two-Way Communication)

- Impact on Project Management and Leadership: 9. How did the implementation of two-way communication systems enhance leadership effectiveness and project management practices in your project?
- Impact on Project Efficiency: 10. To what extent did two-way communication contribute to improving project efficiency by reducing miscommunication or enhancing coordination?

- Impact on Stakeholders Satisfaction: 11. Did the use of two-way communication channels improve stakeholder engagement and satisfaction?
- Impact on Business Success: 12. How did the use of two-way communication systems impact the overall success and business outcomes of your project?

4. Functional Capabilities and Security (Interoperability, Predictive Analytics, Security and Privacy)

- Impact on Project Management and Leadership: 13. How did the interoperability and predictive analytics capabilities of Digital Twin technology influence leadership strategies and project management decisions?
- Impact on Project Efficiency: 14. In what ways did the predictive analytics capabilities improve project efficiency, such as through better forecasting or proactive risk management?
- Impact on Stakeholders Satisfaction: 15. Did the interoperability and data security features of Digital Twin technology lead to greater trust and satisfaction among stakeholders?
- Impact on Business Success: 16. How did the combination of interoperability, predictive analytics, and security features contribute to achieving the project's overall business goals?

Follow-up Comments:

Please indicate your reservations and comments below to help improve the framework.

Vitae

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List of Publications:

- Abdelgadir, H., Mohammed, A (2024). Impact of digital twin on construction project's success. **In preparation.**
- Abdelgadir, H. A Review of the Major Factors of Cost Overrun in Construction Projects, Proceedings of the 7th European Industrial Engineering and Operations Management Conference, Augsburg (Greater Munich), Germany, July 16, 2024, <https://doi.org/10.46254/EU07.20240172>. **Abstract Accepted.**