ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

EXPLORING THE POTENTIAL OF DIGITAL TWIN TECHNOLOGY TO IMPROVE FACTORS AFFECTING CONSTRUCTION PRODUCTIVITY DURING THE CONSTRUCTION PHASE

M.Sc. THESIS

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Department of Architecture

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ISTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

YAPIM AŞAMASINDA İNŞAAT VERİMLİLİĞİNİ ETKİLEYEN FAKTÖRLERİN İYİLEŞTİRİLMESİNDE DİJİTAL İKİZ TEKNOLOJİSİNİN POTANSİYELİNİN İNCELENMESİ

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İrem Komar, a M.Sc. student of ITU Graduate School student ID 502221406, successfully defended the thesis/dissertation entitled “EXPLORING THE POTENTIAL OF DIGITAL TWIN TECHNOLOGY TO IMPROVE FACTORS AFFECTING CONSTRUCTION PRODUCTIVITY DURING THE CONSTRUCTION PHASE”, which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

Thesis Advisor :	**Prof. Dr. Hüsnü Murat GÜNAYDIN** İstanbul Technical University	....
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Date of Submission : 27 April 2025
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To my lovely family and friends,

FOREWORD

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May 2025

İrem KOMAR
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ABBREVIATIONS

AEC	: Architecture, Engineering and Construction
AI	: Artificial Intelligence
ANN	: Artificial Neural Network
AR	: Augmented Reality
BIM	: Building Information Modeling
CAD	: Computer Aided Design
CDT	: Construction Digital Twin
DL	: Deep Learning
DT	: Digital Twin
IFC	: Industry Foundation Classes
IoT	: Internet of Things
ML	: Machine Learning
MR	: Mixed Reality
NASA	: National Aeronautics and Space Administration
RFID	: Radio Frequency Identification
VR	: Virtual Reality

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THESIS EXPLORING THE POTENTIAL OF DIGITAL TWIN TECHNOLOGY TO IMPROVE FACTORS AFFECTING CONSTRUCTION PRODUCTIVITY DURING THE CONSTRUCTION PHASE

SUMMARY

In the construction industry, productivity has been a challenging and significant problem. Despite its significant economic importance, the construction sector often underperforms due to inefficiencies observed across various project stages. Low productivity is caused by a variety of problems, including insufficient communication, labor shortages, inadequate planning and a limited integration of digital technologies. These serious problems eventually decrease the general efficiency and sustainability of construction projects by causing delays, cost overruns, risk factors and resource waste, particularly during the building stage. As a result of these problems the construction sector is becoming more interested in advanced technologies in order to experience a digital transformation. Thus, the industry may achieve better site control, more effective decision making, and improved collaboration. Digital twin (DT) technology is one of these innovations that is currently gaining attention as an exciting concept that could help with major inefficiencies during the building phase. DT makes it possible for virtual and physical environments to synchronize in current time while offering insights based on data for performance enhancement. When integrated with Construction 4.0 technologies such as internet of things (IoT), artificial intelligence (AI), machine learning (ML) and others, DT systems can enable predictive maintenance, better visualization, dynamic planning and modelling construction processes. According to current literature, the DT concept may be particularly beneficial during the building stage since the construction phase is characterized by complicated resource allocation, changing scheduling and critical cost, time and safety performance goals. DT implementation during this stage might facilitate real time site management, decrease rework, enhance safety conditions and allow for a more prepared decision making process. Despite these encouraging advantages, the implementation of DT in the construction stage remains limited, largely due to high costs, technical barriers and lack of awareness.

This research investigates the potential of DT technology to improve productivity in the construction phase by examining how its capabilities align with the factors negatively affecting project performance. To achieve this goal, the objectives of the study are (1) to explore the role of DT throughout the building life cycle in the construction sector (2) to identify its benefits, challenges, and key application areas in the construction stage (3) to determine the factors affecting productivity during the construction phase (4) to compare these factors with the DT system's identified capabilities to assess its potential in overcoming productivity challenges. To accomplish these goals, the research adopts a two step method. First, a comprehensive literature review was conducted to identify the most critical productivity related factors and discover the present knowledge of DT system’s role in construction such as its opportunities, obstacles and major application areas. As a

second step, the questionnaire was designed based on the literature findings to understand the perception of sector experts and distributed to professionals in the construction industry. This resulted in 76 valid responses. The data were analyzed using SPSS v.29. The collected data were analyzed using several statistical methods including descriptive statistics, Cronbach's alpha reliability analysis, normality tests, correlation analysis, independent samples t-tests and one-way ANOVA. These methods enabled a detailed evaluation of relationships between variables and the identification of notable variations in perceptions across participant groups.

Findings from the survey suggest that industry professionals recognize the high potential of DT technology to address key productivity challenges in the construction phase. According to the survey results, professionals identified labor, management systems and design related issues as the most influential and frequently occurring productivity factors. However, when assessing DT system's potential impact, participants believed the greatest improvements would occur in design related issues and management systems. These areas where DT capabilities such as integration with emerging technologies and time, cost optimizations are particularly effective. Despite labor being the most important productivity factor, the associated DT application area workforce monitoring was ranked lowest. This may indicate that DT was not believed to have much of an impact on labor concerns. In the statistical analyses, strong correlations for the benefits of DT concept were found between risk management, real time digital representation and resource management, as well as between time and cost management and resource management. In the challenges of the DT category, the highest correlations appeared among data integration, data management and high-fidelity modeling. For key application areas of DT, strong links were observed between material and equipment management, site monitoring and time and cost optimization.

In addition to descriptive and correlation analyses, the study conducted independent samples t-tests and one-way ANOVA to explore differences in perceptions among participant groups. According to t-tests and ANOVA, there were minor variations between the participant groups. For the t-test, participants were divided into two groups based on their prior knowledge of DT technology (DT-informed and uninformed). Although no significant differences were observed in perceptions of respondents on the productivity factors and the opportunities of the DT system, significant differences emerged in specific areas. Regarding the potential impact of DT on productivity related factors, a statistically significant difference was identified for the communication factor, suggesting that DT-informed participants believed DT implementation could more strongly improve communication during the construction phase. In the challenges, DT-informed participants rated obstacles such as data integration, high-fidelity modeling and the need for skill and training more critically than non-informed participants. Similarly in the key application areas of DT in the construction phase, a significant difference was observed for the enhanced decision making processes variable, where DT-informed participants rated this application area more highly than non-informed participants. For the one-way ANOVA, participants were categorized according to their professional experience: less than 2 years, 2–5 years and more than 5 years. Even though opinions were generally the same among the groups, two notable distinctions were found. First, participants with more than 5 years of experience reported a higher mean score for DT's adaptability performance compared to those with 2–5 years of experience. Second, in the integration with the emerging technologies application area, those with more than 5 years of experience again rated the application area significantly higher compared to participants with 2–5 years of experience. These findings may imply that more experienced professionals tend to perceive a more positive view of DT as more adaptable and better suited for integration with advanced technologies in construction processes.

According to the results obtained from the study, industry experts are optimistic about the DT technology and believe that it can significantly influence the factors determining efficiency and positively affect the productivity in the construction phase.

TÜRKÇE YAPIM AŞAMASINDA İNŞAAT VERİMLİLİĞİNİ ETKİLEYEN FAKTÖRLERİN İYİLEŞTİRİLMESİNDE DİJİTAL İKİZ TEKNOLOJİSİNİN POTANSİYELİNİN İNCELENMESİ

ÖZET

İnşaat sektöründe verimlilik, bu alanda uzun süredir hem önemli hem de zorluk teşkil eden bir problem olarak görülmektedir. Ekonomik açıdan büyük önem taşımasına rağmen, inşaat sektörü çoğu zaman proje süreçlerinin çeşitli aşamalarında gözlemlenen verimsizlikler nedeniyle düşük performans sergilemektedir. Düşük verimlilik, yetersiz iletişim, iş gücü eksiklikleri, yetersiz planlama ve dijital teknolojilerin sınırlı entegrasyonu gibi çeşitli sorunlardan kaynaklanmaktadır. Özellikle yapım aşamasında ortaya çıkan gecikmeler, maliyet aşımı, risk unsurları ve kaynak israfı gibi etkiler sonucunda bu sorunlar inşaat projelerinin genel verimliliğini ve sürdürülebilirliğini olumsuz yönde etkilemektedir. Bu sorunlar nedeniyle, sektör dijital dönüşüm sürecine yönelik olarak ileri teknolojilere giderek daha fazla ilgi göstermektedir. Bu bağlamda sektör, şantiye kontrolü ve izleme, karar alma süreçleri ve iş birliğini iyileştirme yönünde ilerleme kaydedebilir.

Bu teknolojik yenilikler arasında yer alan dijital ikiz (DT) teknolojisi, özellikle yapım aşamasındaki ciddi verimsizlikleri giderebilecek potansiyele sahip, dikkat çekici bir kavram olarak öne çıkmaktadır. DT teknolojisi, sanal ve fiziksel ortamlar arasında eş zamanlı senkronizasyon sağlayarak performans iyileştirmeye yönelik veri temelli içgörüler sunar. Nesnelerin interneti (IoT), yapay zeka (AI), makine öğrenmesi (ML) gibi Endüstri 4.0 teknolojileriyle entegre edildiğinde, DT sistemleri tahmine dayalı bakım, gelişmiş görselleştirme, dinamik planlama ve inşaat süreçlerinin modellenmesini mümkün kılmaktadır. Güncel literatüre göre, DT kavramı özellikle yapım aşamasında önemli faydalar sunabilir; çünkü bu aşama, kaynak tahsisi, değişken zaman tahmini ve maliyet, zaman, güvenlik hedefleri açısından en karmaşık süreçlerin yaşandığı dönemdir. Bu teknoloji sayesinde, şantiye yönetimi gerçek zamanlı olarak yürütülebilir, yeniden iş yapma oranı azaltılabilir, güvenlik koşulları iyileştirilebilir ve daha hazırlıklı bir karar alma süreci sağlanabilir. Ancak bu avantajlara rağmen, DT'nin yapım aşamasındaki uygulamaları hala sınırlıdır, bunun başlıca nedenleri arasında yüksek maliyetler, teknik engeller ve farkındalık eksikliği yer almaktadır.

Bu çalışma, DT teknolojisinin yapım aşamasında verimliliği artırma potansiyelini araştırmakta ve bu teknolojinin yeteneklerinin, proje performansını olumsuz etkileyen faktörlerle ne derece örtüştüğünü incelemektedir. Bu amaç doğrultusunda çalışmanın hedefleri şunlardır: (1) DT'nin inşaat sektöründeki yapı yaşam döngüsü boyunca oynadığı rolü incelemek, (2) Yapım aşamasındaki avantajlarını, zorluklarını ve önemli uygulama alanlarını belirlemek, (3) Yapım aşamasında verimliliği etkileyen faktörleri ortaya koymak, (4) Bu faktörleri DT sisteminin özellikleri ile karşılaştırarak, söz konusu teknolojinin verimlilik sorunlarını çözmedeki potansiyelini değerlendirmektir.

Bu hedefleri gerçekleştirmek amacıyla iki aşamalı bir yöntem benimsenmiştir. İlk olarak, verimlilik ile ilişkili temel faktörleri ve DT sistemlerinin inşaat süreçlerindeki rolünü, fırsatlar, zorluklar ve uygulama alanları gibi, belirlemek amacıyla kapsamlı bir literatür taraması yapılmıştır. İkinci aşamada ise, literatür bulgularına dayanarak uzman görüşlerini anlamaya yönelik bir anket formu hazırlanmış ve inşaat sektörü profesyonellerine uygulanmıştır. Anket sonucunda 76 geçerli yanıt elde edilmiştir. Veriler SPSS v.29 yazılımı kullanılarak analiz edilmiştir. Sonrasında ise tanımlayıcı istatistikler, Cronbach's Alpha güvenilirlik testi, normallik testleri, korelasyon analizi, bağımsız örneklemler t-testi ve tek yönlü ANOVA gibi çeşitli istatistiksel yöntemler uygulanmıştır. Bu analizler, değişkenler arası ilişkilerin ve katılımcı gruplar arasında algı farklılıklarının detaylı biçimde değerlendirilmesine olanak sağlamıştır.

Anket bulguları, sektör profesyonellerinin DT teknolojisinin yapım aşamasındaki temel verimlilik sorunlarını çözme konusunda yüksek bir potansiyele sahip olduğunu düşündüklerini ortaya koymaktadır. Katılımcılar, iş gücü, yönetim sistemleri ve tasarıma bağlı konuları en etkili ve en sık karşılaşılan verimlilik faktörleri olarak tanımlamıştır. Ancak DT sisteminin potansiyel etkileri değerlendirildiğinde, katılımcılar en büyük iyileştirmenin tasarım kaynaklı sorunlar ve yönetim sistemlerinde gerçekleşebileceğini belirtmiştir. Bu durum, DT'nin özellikle yeni teknolojilerle entegrasyon ve zaman, maliyet optimizasyonu gibi yeteneklerinin bu alanlarda etkili olduğunu göstermektedir. Öte yandan, iş gücü en önemli verimlilik faktörü olarak görülmesine rağmen, bu faktöre karşılık gelen DT uygulama alanı olan işgücü takibi en düşük sırada yer almıştır. Bu da DT'nin iş gücü sorunlarına yönelik etkisinin sınırlı algılandığını göstermektedir.

İstatistiksel analizler kapsamında, korelasyon analizinde, DT'nin faydalarına ilişkin olarak risk yönetimi, gerçek zamanlı dijital temsil ve kaynak yönetimi arasında, ayrıca zaman ve maliyet yönetimi ile kaynak yönetimi arasında güçlü korelasyonlar gözlemlenmiştir. Zorluklar kategorisinde en yüksek korelasyon veri entegrasyonu, veri yönetimi ve yüksek doğruluklu modelleme arasında bulunmuştur. Önemli uygulama alanlarında ise malzeme ve ekipman yönetimi, şantiye izleme ve zaman, maliyet optimizasyonu arasında güçlü ilişkiler belirlenmiştir.

Tanımlayıcı ve korelasyon analizlerine ek olarak, bağımsız örneklemler t-testi ve tek yönlü ANOVA analizleri de yapılmıştır. T-testinde katılımcılar, DT hakkında bilgi sahibi olanlar ve olmayanlar şeklinde iki gruba ayrılmıştır. DT teknolojisinin faydaları ve verimlilik faktörleri konusunda gruplar arasında anlamlı bir fark bulunmazken, belirli alanlarda farklılıklar gözlemlenmiştir. Özellikle, iletişim faktörü için DT'den haberdar katılımcılar, teknolojinin bu alanda daha yüksek katkı sağlayacağını düşünmektedir. Ayrıca, veri entegrasyonu, yüksek doğruluklu modelleme ve beceri, eğitim ihtiyacı gibi zorluklar da DT bilgisine sahip katılımcılar tarafından daha eleştirel biçimde değerlendirilmiştir. Uygulama alanlarında ise geliştirilmiş karar alma süreçleri değişkeni anlamlı fark göstermiştir, DT bilgisi olanlar bu uygulamayı daha etkili görmektedir.

ANOVA analizinde katılımcılar, mesleki deneyimlerine göre üç gruba ayrılmıştır: 2 yıldan az, 2–5 yıl ve 5 yıldan fazla deneyimi olanlar. Genel olarak benzer görüşler bildirilse de iki önemli farklılık tespit edilmiştir. Beş yıldan fazla deneyime sahip katılımcılar, adaptasyon yeteneği ve yeni teknolojilerle entegrasyon uygulama alanlarını diğer gruplara kıyasla daha yüksek puanlamıştır. Bu bulgular, deneyimli profesyonellerin DT teknolojisinin gerçek hayatla adaptasyon ve ileri teknolojilerle entegrasyonu konularında daha olumlu bir bakış açısına sahip olabileceğini göstermektedir.

Çalışmadan elde edilen sonuçlara göre sektör uzmanları, DT teknolojisine iyimser yaklaşmakta ve bu teknolojinin verimliliği belirleyen temel faktörler üzerinde olumlu etkiler yaratabileceğine inanmaktadır.

1. INTRODUCTION

Productivity remains one of the most critical, complicated and persistent issues in the construction industry. The productivity performance of the sector has remained below that of other important industries despite making an enormous economic contribution (Turner et al., 2021; Laszig et al., 2020Therefore, the industry continues to experience low levels of efficiency, frequent delays and high resource waste. Numerous studies have identified a number of variables that adversely affect construction productivity, including inadequate planning, poor communication, insufficient skills, shortages of workers, technological diversity, material waste and safety incidents (Mehta et al., 2022; Hasan et al., 2018; Ghoddousi and Hosseini, 2012). Additionally, the complex and multidisciplinary nature of construction projects, together with uncertainties and constant changes, leads to cost overruns, project delays and poor employee output, particularly during the construction phase. Contributing factors such as delayed digitalization and innovation resistance intensify the productivity gap in the sector. Moreover, the lack of real time information, unconnected systems and a restricted usage of smart technologies during operation phases contributes to the sector's strong productivity challenges. Furthermore these inefficiencies constrain financial results, achievement of time, cost, quality and sustainability standards (Teisserenc and Sepasgozar, 2021; Naoum, 2016). Due to these consistent difficulties, the construction sector has been growing attention to digital transformation with the goal of improving performance. These persistent inefficiencies have created a requirement for advanced digital technologies that can enhance coordination, monitoring and management methods during construction processes. Within this context, digital twin (DT) technology has emerged as a highly exciting development. Among the most recent digital solutions, DT technology has gained significant attention for its ability to establish a real time data connection between the physical and virtual worlds (Wang et al., 2021; Liu et al., 2022). The data flow enables continuous synchronization for monitoring, simulation and optimization purposes (Boje et al., 2020). Through integration with internet of things (IoT), artificial intelligence (AI), deep learning (DL), machine learning (ML) and other innovative technologies, DT systems can process large datasets, predict outcomes and provide feedback for ongoing performance improvement in a project's life cycle (Elfarri et al., 2022; Lu et al., 2020a; Austin et al., 2020). DT allows stakeholders to calculate possible hazards and make data driven decisions early in the project. In addition, it provides real time visualization and predictive monitoring. This helps reduce interruptions and improve planning by offering an extensive overview of site conditions and activities. Additionally, DT provides a number of advantages, including life cycle cost reductions, enhanced safety performance, energy optimization, predictive maintenance and sustainability benefits from more effective resource usage. These advantages support long term environmental goals as well. Compared to other industries, the architecture, engineering and construction (AEC) sector has adopted the DT concept more recently. The most common applications are observed in the operation and maintenance stages of the building lifecycle (Almatared et al., 2022). However, the construction phase presents significant opportunities for DT implementation (Opoku et al., 2021; Boje et al. 2020). As Yang et al. (2024) emphasize that this phase involves the high level of complexity in management systems such as resource allocation, time, quality and cost. According to Piras et al. (2024) and Almatared et al. (2022), DT appears as a system that may handle this complexity since it works effectively when combined with advanced technologies to provide dynamic and intelligent construction site modeling. However, as Construction 4.0 encourages the digital transformation of the industry, there is rising interest in implementing DT (Moshood et al., 2024). This is particularly during the construction phase, when its productivity boosting effects could be most effective. In this phase, DT technologies have the potential to address several inefficiencies. DT might encourage faster decision making and minimize rework, delays and safety hazards by providing real time site condition viewing, automated progress tracking, material and labor monitoring and construction simulation. These capabilities align closely with key productivity factors. According to Bosch-Sijtsema et al. (2021), by facilitating more accurate simulations and data based systems, DT has the capacity to directly address factors influencing productivity such as time, cost, safety and quality. Furthermore, DT increased its ability to improve collaboration among project stakeholders, decrease waste and optimize processes by integrating with tools like robotics, big data analytics and building information modeling (BIM) (Bosch-Sijtsema et al., 2021; Sepasgozar et al., 2021). The potential of DT and its increasing demand to improve construction productivity is frequently highlighted in the literature. Nevertheless, the implementation of DT technologies during the construction phase is in early stages. This technology is a valuable approach to overcoming persistent inefficiencies by promoting connectivity, automation and adaptability in construction processes. The relationship between DT technology and productivity is an important area for the future of the construction sector.

1.1 Purpose of the Study

According to existing literature, DT is most commonly applied in the operation and maintenance phase of the building lifecycle (Almatared et al., 2022). Boje et al. (2023) state that the DT of a structure starts to take form during the construction phase, but it reaches more advanced degrees of development during its operational stage. However, Yang et al. (2024) emphasize that the performance of the construction phase directly affects key project outcomes such as quality, schedule, cost and safety efficiency. In line with this, Akanmu et al. (2021) highlight the significance of the construction stage, claiming that DT is essential for optimizing several project lifecycle processes during this phase. Similarly, Boje et al. (2020) argue that the adoption of the DT concept in the construction phase has the capacity to revolutionize the construction industry. Building on this perspective, the study focuses on the potential of DT in the construction phase by addressing the factors that negatively impact productivity during this stage. It examines how DT capabilities correspond to these challenges by identifying its advantages, main obstacles to its adoption and significant usage areas. Thus it may contribute to a deeper understanding of its role in enhancing project performance. More generally, the study investigates the relationship between DT technology and productivity in the construction phase by identifying the key productivity related factors and assessing how DT's capabilities may contribute to addressing these challenges. Through a combination of literature review and survey analysis, the research tries to provide insights into the potential role of DT in enhancing efficiency in the construction phase. To achieve this purpose, the research objectives are:

1) To explore the role of DT throughout the building life cycle in the construction sector
2) To identify its benefits, challenges, and key application areas in the construction stage
3) To determine the factors affecting productivity during the construction phase
4) To compare these factors with the DT system's identified capabilities to assess its potential in overcoming productivity challenges

1.2 Scope of the Study

This study focuses on the possible role of DT in responding to productivity challenges in the construction stage. Therefore the scope is limited to the construction phase of the building life cycle. Also the research is based on a comprehensive literature review and a survey conducted with professionals from the local construction industry. The study discusses how DT could assist in reducing these inefficiencies through an analysis of capabilities of DT technology and alignment with productivity factors. Since DT technology is still in its early stages of adoption within the construction sector, the survey stage of the study mostly reflects expert opinions and projections rather than direct evaluations based on practical experience.

1.3 Method of the Study

In order to achieve the objectives, this study combines a comprehensive literature review and a quantitative survey. The literature review was conducted to identify main productivity factors in the building stage as well as to examine the advantages, challenges in adoption and major usage areas of DT systems in the same phase. Based on the findings from the literature, a questionnaire was developed to collect data from experts. The survey intended to discover perceptions of participants about DT and their opinions on its possible contributions to improving productivity in the construction phase. The data collected were analyzed using descriptive statistics, reliability tests, normality test , correlation analysis, independent samples t-test and one-way ANOVA. Then the data is examined in order to find relationships and assess differences.

2. LITERATURE REVIEW

2.1 Digital Twin

A digital twin (DT) is a dynamic virtual representation of real world properties through the use of actual time data obtained from sensors (Boje et al., 2020; Opoku et al., 2021; Liu et al., 2021). Simply, DT is the combining of information between an actual object and its virtual replica that functions in both directions (Fuller et al., 2020). The DT consists of 3 main parts: the real world twin, the virtual world twin and the connection that links twins with information and data flow (Rasheed et al., 2020; Nguyen and Adhikari, 2023; Teizer et al., 2022). Also DT varies with 3D modeling in terms of being current and having information exchange (Elfarri et al., 2022; Jiang et al., 2021). DT technology was mentioned in 2003 by Grieves who was the first person to describe the DT concept, and he was working on product lifecycle management (Boje et al., 2020; Liu et al., 2021; Akanmu et al., 2021). At the beginning, the concept did not garner significant attention or engagement during that period (Wang et al., 2022). However nowadays as data generation from sensors and communication technology develop, the concept of the DT is gaining success and becoming popular (Wang et al., 2021; Liu et al., 2021; Kim and Ham, 2022). NASA played a significant role by releasing a paper in 2012 and took an important step in defining the framework of DT (Fuller et al., 2020; Khajavi et al., 2019). In that study conducted by Glaessgen and Stargel (2012) in NASA they mentioned the DT as a combined and complex simulation of a real vehicle or system, that includes various physical factors and probabilities. It utilizes the most accurate physical models, data from sensors, historical fleet information and more to replicate the entire operational lifespan of its real-world twin. DT is currently one of the main and developing technological advancements for Industry 4.0 and the upcoming Industry 5.0 (Lauria and Azzalin, 2024). Sun et al. (2022) emphasize studies in this field have intensified in recent years. They emphasize that not only the visual parameters taken from the physical object are transferred to the DT, but also data containing all kinds of information is transferred, and as a result, a virtual representation consisting of multidimensional information is created. Researchers further discuss, the purpose of a DT is to provide information and insight when making decisions and taking action about the physical item. Likewise Zhuang et al. (2018) state DT includes virtual data that provides a description of a physical object, spanning from the details to the larger geometric aspects to express the multiplicity of data collected. Wang et al. (2022) explain, DT uses digital methods including the creation of tools, simulations, IoT devices and VR to translate the various characteristics of real world equipment into virtual environments. This process creates a digital replica that can be taken apart, adjusted and used multiple times. The method boosts a person's understanding of objects. Similarly Liu et al. (2021) indicate, in the building sector, DT offers multiple levels of information, visualization, analyzing and estimation. Through the use of DT, customers may see all of the details they need about the physical construction, which improves comprehension and communication. It is also capable of processing information well. Furthermore, data mining is a way to generate new knowledge from huge data sets if fresh data are made accessible through DT. Condition analysis and other emergency management procedures can benefit greatly from this. In summary, Jiao et al. (2024) highlight DT is a key digital tool for the construction sector, enhancing operation efficiency and quality. Additionally, Boje et al. (2020) approach this topic from a sustainability perspective, stating that advancing clean energy and low carbon emission goals is how the significance of working with DT is determined. Figure 2.1 explains the working principle of the DT between the real world and the visual representation. The four interaction relationships between both the physical and digital worlds have been simplified into a conceptual framework.

In examining the DT and Building information modeling (BIM) relationship, they are both representations of actual assets, but due to the differences in their functions and capabilities, DT of structures could be thought of as a version of BIM+, which was created from digital descriptions (Wang et al., 2022). Autodesk (2023) expresses that the BIM process combines data from planning and design, while DT captures information throughout the construction and operational phases of the asset, enabling the prediction of future projects. Abilities to communicate distinguish DT apart from 3D modeling and these skills are a necessary component of DT (Wang et al., 2021).

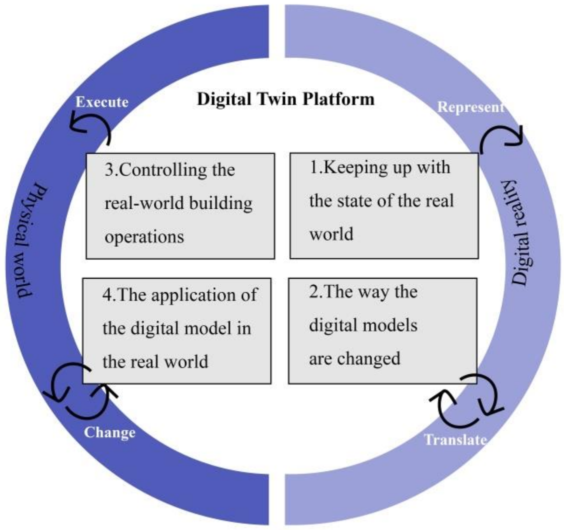

Figure 2.1 : The digital twin platform's structure adapted from Sun et al. (2022).

Khajavi et al. (2019) claim, BIM is mainly employed to avoid errors in the building design process, enhance communication among stakeholders, boost construction efficiency and track the time and cost of construction projects. In contrast, DT has purposes such as predictive maintenance, improving resource efficiency, enhancing tenant comfort, conducting what-if analyses for optimizing building design and enabling closed-loop design to transfer insights from one building to future ones. DT has the capability to be constantly updated to mirror real time changes in the physical object, and they can utilize predictive analytics to anticipate future conditions unlike to BIM (Elfarri et al., 2022). Boje et al. (2020) point out that in the building sector, there are a number of restrictions on BIM. Its lack of IoT connection is one of its primary weaknesses. Also BIM has a static and closed data system, while DT offers an interactive accessible online workspace that includes internet of things (IoT) integration and advanced artificial intelligence (AI) capabilities. BIM also stays poorly in the areas of automation and interoperability. They emphasize further, BIM helps professionals create a regular way to represent building parts and systems. In contrast, the DT analyzes the wider picture by considering the social and technical aspects of complex objects. It does this by using real time data connections between the digital and physical worlds. Researchers also highlight, in the relationship between physical and virtual aspects of DT, BIM is often seen as a part of it. These elements that DT have can assist in resolving BIM's constraints and giving the building sector a more complete and useful tool. BIM is a process centered on 3D modeling that provides architects, engineers and construction experts with the means to effectively plan, design, build and oversee buildings and infrastructure in a more efficient manner (Eastman et al., 2011). According to Succar (2008), BIM serves as a realistic visual representation of a building that may be utilized for design, planning and construction phases. However, it is primarily employed during the design and building stages of a project. On the other hand, DT technology is a lively, real time digital copy of a real item or system using sensor data to represent the current condition of the actual item (Tao et al., 2018). The research community is currently shifting its attention from BIM applications to DT applications and the challenge lies in the fact that the BIM model is disconnected between physical and virtual objects, whereas DT intends to deal with this by creating a strong, two-way integration link (Almatared et al., 2022). Nonetheless, the adoption of DT technology remains at an early developmental phase (Boje et al., 2020). In brief, although both BIM and DT offer digital representations of real property, BIM focuses mainly on design and construction, whereas DT further by providing continuous tracking, analysis and predictive purposes throughout an asset's lifecycle (Wang et al., 2022; Elfarri et al., 2022; Liu et al., 2021; Tao et al., 2018). This shift from BIM to DT improves monitoring, oversight and decision making abilities over a structure's existence (Mashood et al., 2024).

2.1.1 Technologies supporting digital twin implementation

Advancements in technology have revolutionized the construction sector by integrating machines, sensors and intelligent systems into the planning, building and monitoring processes (Si et al., 2023). DT integrates several industry 4.0 technologies to the building industry, such as data collection and processing, modeling and simulation, tools for decision support systems (Moshood et al., 2024). In relation to this there are many technologies that help DT to operate (Piras et al., 2024). Some of them are IoT (Sethi et al., 2017; Sun et al., 2022), AI (Elfarri et al., 2022; Al Musaed and Yitmen, 2023), Model Visualisation (Elfarri et al., 2022; Sun et al., 2022), Immersive Technologies (Yang et al., 2024; Piras et al., 2024), Deep Learning (DL) & Machine Learning (ML) (Wang et al., 2022; Austin et al., 2020; Lu et al., 2020a), Sensor Technology (Riaz et al., 2015; Austin et al., 2020; Ham and Kim, 2020), Cloud Platforms & Data Storage (Ying et al., 2019; Fuller et al., 2020). Together, these technologies form the foundation of the DT structure and enable producing precise, dynamic and current time digital replicas (Yang et al., 2024).

Austin et al. (2020) and Akanmu et al. (2021) insist the key components of a successful DT system are cloud computing, IoT and semantic modeling. On the other hand, Yang et al. (2024) claim technologies like blockchain, cloud computing, big data and simulation are viewed as additions and enhancements to the DT structure, giving the system more features and abilities.

The IoT refers to the integration of internet connectivity into various devices, giving them the ability to collect information about their environment (Yang et al., 2024). Fuller et al. (2020) state the escalating number of IoT devices, which surpassed 17 billion in 2018, indicates the technology's significant development. According to their projections, there will be more than 75 billion of these devices in use by 2025, and the industry will be worth more than $5 trillion. Likewise Teisserenc and Sepasgozar (2021) mention, in construction areas, IoT may result in annual savings of between $160 billion and $930 billion. Madni et al. (2019) point out the increase in connectivity fits with the idea of a connected environment on a global scale. Additionally they explain it has positive effects on a variety of industries, including daily life, communication, healthcare, construction, transportation, smart cities, smart homes, wearables and manufacturing. Sun et al. (2022) indicate the IoT plays a crucial role in the DT platform. IoT devices, collect status data from physical objects and transmit this data for further analysis. This real time data stream enables functions such as accurate and real time monitoring. BIM and IoT have the potential to provide technological support for managing building operations through the DT. Also they add the automated procedures and IoT devices are needed for effective time management. Similarly Vemulapalli et al. (2021) claim to have the full potential of DT, it requires a convergence of the modern technologies such as AI and IoT. Also they express the effectiveness of DT technology in the IoT network lies in its ability to create a virtual representation of a physical object. Moreover they state the technologies should be standardized for their applications and long-term viability. In a similar way Sethi et al. (2017) mention IoT devices are vulnerable to cyber attacks, because the data they collect can be sensitive. Therefore, it is essential to ensure that the data is secure and that the privacy of the users is protected. Also it's crucial to properly handle the huge amount of data that IoT devices produce. Furthermore IoT devices are battery-powered and have minimal compute and storage resources. Communication of data between devices is a power consuming task, especially wireless communication. Therefore, researchers discuss the need for a solution that facilitates communication with low power consumption. On the other hand IoT devices can help in cost savings by reducing energy consumption and improving the efficiency of various processes.

The fundamental concept of AI and its general definition originated in the late 1950s, focusing on the creation of intelligent systems (Fuller et al., 2020). Almatared et al. (2022) express AI as one of the major fields of DT research and add that it is crucial in helping project managers improve their choices that have an impact on costs, time and effort. They also indicate AI plays a crucial role in decision making and in the context of DT it enhances predictive analysis capabilities. They emphasize that while DT often relies on simulation for predictions, the integration of AI can significantly improve decision making within the architecture, engineering and construction (AEC) field. Numerous studies found that the DT was assisted by IoT, making AI a crucial element to enable the DT for prediction and better decisions (Boje et al., 2020). Elfarri et al. (2022) state AI, along with sensor technologies and virtual reality (VR), is examined to provide real time information about various aspects of the house such as air quality, water leakage, occupancy and external weather conditions. They claim AI is used to develop a DT of a construction. For this reason in their study, they created a fully functional and highly capable DT of a contemporary home by combining AI, innovative sensor technology and VR. Almusaed and Yitmen (2023) point out AI simulations and DT are employed in the design and management of tasks, structure and operations for the next era of constructions, with the aim of improving user satisfaction and optimizing building efficiency. The idea of applying AI in the construction of smart buildings is becoming more and more popular as technology, particularly the IoT continues to advance. These models reflect various design possibilities and estimate their implications. Also they assess the building's performance and methods to enhance both user comfort and building efficiency. Moreover artificial neural networks (ANN) have several advantages over traditional techniques and may be utilized to develop and operate intelligent building systems. Furthermore they mention that only a few of the many capabilities of ANN in information processing include instability, resilience, fault and failure tolerance, learning and managing uncertain and complex data.

Regarding model visualization, Elfarri et al. (2022) indicate that 3D modeling involves the use of software to create a three-dimensional representation of an object, commonly referred to as a computer-aided design (CAD) model. This model is composed of points, edges and surfaces, which collectively create a visual simulation of physical objects. Also 3D rendering is a digital graphics technique where textures are applied to the surfaces of a 3D model, resulting in a lifelike and photorealistic appearance of the object. Furthermore they mention the importance of 3D modeling in creating a DT. Sun et al. (2022) add that the precise recreation of physical items in a high-fidelity digital model is the central component of a DT system. For the DT to gain some kind of management over the actual environment, the visualization is a crucial tool. This model includes multi-dimensional object status data and is capable of being used for simulations and visualization, among other things. The BIM model and application use a complex model and place a spotlight on collaboration, which may meet the necessities of the DT model. Due to the multifaceted nature of the building environment and the numerous services it offers, monitoring and controlling it using a single digital replica is challenging. To address this, multiple BIM models are generated from the original BIM files. These models store specific information and function independently to handle various aspects effectively.

In the context of immersive technologies, technology that switches out the actual world with a fully virtual environment is VR, improves it with simulation is augmented reality (AR), or combines the two is mixed reality (MR) (Salih and El-adaway, 2024). Yang et al. (2024) claim that VR offers a wide range of uses in construction over the lifespan of a project. It enables architects to totally immerse into the design process, assessing lighting, materials and set up. Also they emphasize VR and AR may offer both interactive and immersive usages by combining BIM, IoT and other innovations. They further discuss AR has lasting significance in the construction industry, particularly when combined with tools for identifying and visualizing environmental abnormalities in building projects. Incorporating VR/AR with BIM is anticipated to improve project awareness by allowing users to virtually enter buildings, simplify onsite manufacturing with less errors and more (Pan et al., 2021a). Additionally, AR enhances construction visualization by overlaying digital data in the physical world, while VR creates simulated work settings for detailed planning and education by offering virtual supervision throughout the construction stages (Pan et al., 2021b; Sabet and Chong, 2020). Moreover, immersive technologies promote safety and risk management during the construction stage, help with employee education and simulate the process of construction (Pan et al., 2021b; Piras et al., 2024). Furthermore, these tools enable people to experience actual job conditions previous to project finish (Piras et al., 2024). As Sabet and Chong (2020) point out VR/AR facilitate automation, reduce flaws and improve security by allowing virtual site inspections to see possible hazards. Also VR offers an environment that can enhance satisfaction between stakeholders as well as work excellence by providing detailed visuals and improved comprehension of project participants (Yang et al., 2024; Sabet and Chong, 2020). Salih and El-adaway (2024) offer significantly, demonstrating that AR and VR are one of the essential players in time savings. Additionally, their study shows an intense connection among DT and AR/VR.

ML, a subset of AI, is the development of technologies that can enable the computer to acquire knowledge and make decisions on behalf of the user without being explicitly programmed to do so and deep learning is an element of machine learning (Fuller et al., 2020). DT combines AI, ML and data analytics to build interactive digital simulations that can represent and forecast the present and future states of reality while also learning from a variety of sources (Lu et al., 2020a). Wang et al. (2022) identify DL as a simple neural network with three or more layers. They claim deep learning enables DT to evolve from static digital duplicates into dynamic instruments capable of learning, adjusting and optimizing. DT are created and run using DL as a core technology. Also they state that deep learning, as a subset of machine learning, has the capacity to examine the extensive data gathered by DT for prediction, operational enhancement and facilitating the self-improvement and adaptability of DT over time. As researchers state numerous AI programs and services rely on DL to increase automation and carry out both physical and mental duties without any human participation. In their study, in order to evaluate inhabitants' environmental peacefulness, the deep learning approach is used to evaluate the impact of DT applications in intelligent buildings. Austin et al. (2020) point out the operation and optimization of the DT system greatly benefits from machine learning. ML systems can examine data gathered from physical objects or their surroundings and use it to estimate outcomes or discover movements.

Furthermore it gives the DT the analytical capability required to make insightful conclusions from the data it has acquired, improving its ability to reflect and monitor the condition of the real world item or system.

Sensor technology involves employing a variety of sensors to identify and react to specific signs in the physical surroundings, such as light, temperature, movement, moisture, pressure, or numerous other environmental factors. (Riaz et al., 2015; Austin et al., 2020). Austin et al. (2020) indicate sensor technology is essential for both building and running a DT. Sensors that are integrated into the physical object or its surroundings gather real time information regarding different aspects and variables. This information is afterward sent to the DT, which utilizes it to adjust its condition and actions to mirror those of the physical counterpart. They discuss, sensor technology acts as the crucial data bridge connecting the physical object to its DT, ensuring the digital representation accurately mirrors the current status of the real-world counterpart. This makes it possible to observe, assess and improve the physical system or object in real time using its DT. As Riaz et al. (2015) point out, nevertheless, sensor data flows will provide challenges for conventional approaches to data management due to the enormous amounts of data. Similarly Ham and Kim (2020) mention the challenges that may present an issue, and one of them is the precision of the gathered data, which can impact the overall dependability of both the collected data and the subsequent analysis. Additionally, the process of gathering data can be lengthy and may lead to notable reluctance or discomfort among participants, particularly in participatory sensing methods. This might influence the extent to which these technologies can be effectively utilized.

Ying et al. (2019) mention that cloud technology involves employing distant servers on the internet for data storage, management and processing, instead of relying on local servers or personal computers. This offers users the ability to access data and applications from any location with an internet connection, enabling advantages like capacity, adaptability and cost-efficiency. They further state DT technology typically utilizes cloud computing for the storage and processing of extensive data. This technology requires generating a virtual duplicate of a physical entity or system, enabling examination, modeling and optimization. As they indicate, collecting and processing the substantial data essential for this purpose can be achieved more efficiently and economically by taking advantage of cloud computing resources.

Moreover researchers emphasize, cloud technology facilitates universal access to DT models and services via an internet connection, simplifying collaboration and information sharing among multiple locations and organizations. Additionally Akanmu et al. (2021) assert that the amount and diversity of DT data make traditional databases unsuitable for storing it, which leads to growing interest in big data storage options like cloud platforms.

The technologies that contribute to the formation and operation of the DT are visualized in Figure 2.2. By combining these technologies, DT creates interactive virtual worlds that can predict and depict the current and future situations of reality. Also how these different technologies contribute is briefly described in the figure. Moreover each technology is rapidly evolving so it is directly increasing the potential of the DT in this process.

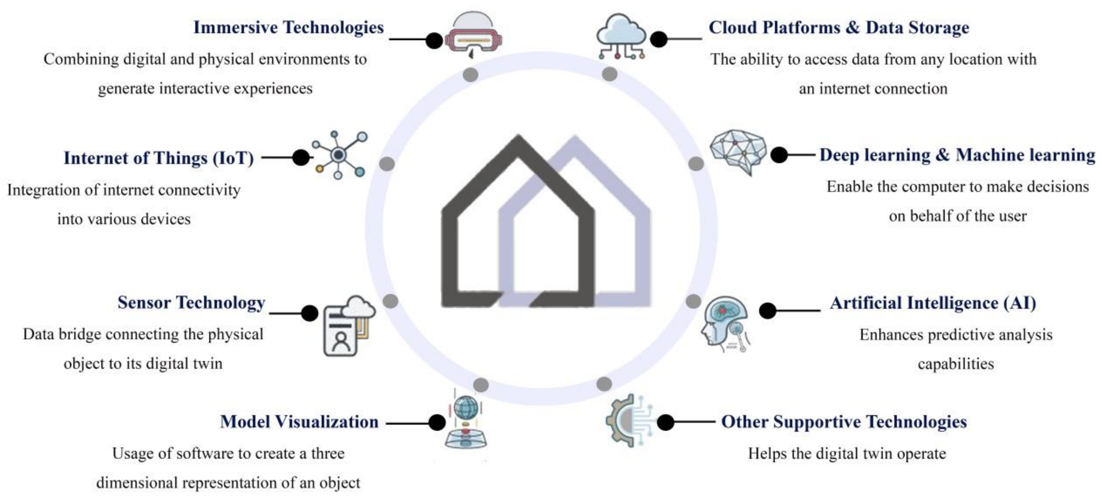

Figure 2.2 : Technologies form the foundation of the digital twin system.

The use of DT solutions is growing in popularity as the construction industry looks to increase effectiveness and competitiveness (Moshood et al., 2024; Laszig et al., 2020). This strategy makes use of Industry 4.0 technologies customized for the building sector (Moshood et al., 2024). Figure 2.3 examines the ways in which these technologies assist the 4 defining features of DT: data acquisition, data processing, modeling and simulation and decision support enablers. Data acquisition is gathering unprocessed data and sending it to the database or cloud-based system using essential technologies. Data processing is crucial in order to effectively model and analyze large, live databases and turn them into useful information. 3D models and simulations are employed in modeling and simulation, two essential components of

DT technologies, to view and evaluate scenarios. Decision support enables construction systems to handle interruptions and guarantee seamless lifecycle transitions by using AI and semantic tools.

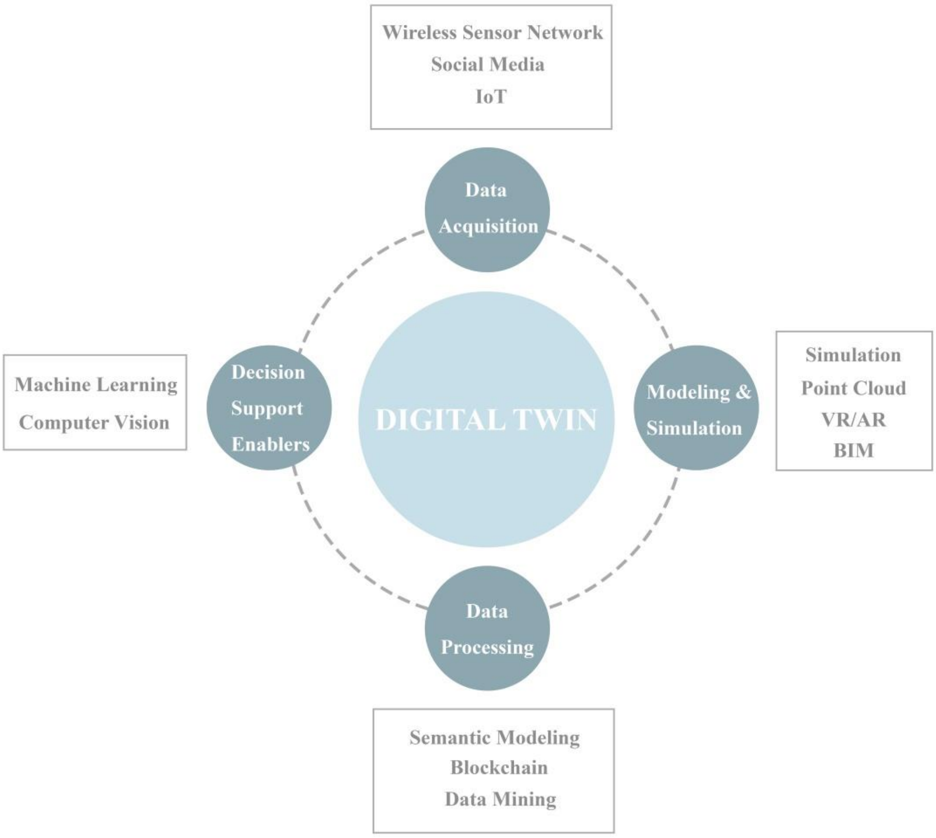

Figure 2.3 : 4 fundamental characteristics of the DT system adapted from Moshood et al. (2024).

2.1.2 Digital twin in diverse industry contexts

Other than building applications there are some other areas such as transportation, scheduling, adaptive traffic control, production, healthcare, smart city and aerospace industry. DTs are used by a variety of industrial sectors to improve the management of physical assets, physical systems and production processes (Wang et al., 2022). Manufacturing, aerospace industry, healthcare and infrastructure systems are the industries that benefit from the DT (Azfar et al., 2023; Akanmu et al., 2021).

Azfar et al. (2023) mention that it has been proven in a study conducted in Atlanta that the use of DT in city transportation increases driving safety and reduces transportation time. In the study called North Avenue Smart Corridor, traffic flow was tried to be regulated effectively by using IoT and cameras, so a better environment was created for pedestrians, cyclists and car drivers. Sensors detect vehicles and pedestrians and transfer their location to the 3D model whereas cameras transfer traffic density information to the digital model. As a result, AI synchronizes guiding elements such as traffic lights and regulates traffic flow. Apart from this, the model, which receives data from car driving, can also learn information about driving, leading to a better functioning transportation idea for the future.

Deria et al. (2022) examined the DT to explore the feasibility of automatically generating the best work scheduling and planning resource allocation for pavement in roadway construction sites. Thus, they expect it to provide benefits by reducing the need for human labor, human error and unproductive times in the work plan in road construction.

As an example of sensor usage in traffic, The Istanbul Metropolitan Municipality Transport Department (2018) created the adaptive traffic management system to minimize traffic density and boost traffic flow in Istanbul. This system dynamically regulates traffic based on the real time density of vehicles at intersections. Initially, magnetic sensors at crossings count vehicles and send data to the intersection's traffic signal controller. Then the controller transmits it to the adaptive traffic management system, managed by the transportation management center. Using a real time optimization algorithm, the system calculates traffic density and adjusts green light durations for each direction.This results in reducing delays by %15 to %30 when compared to traffic data from intersections where the adaptive traffic management system is not employed. This improvement leads to a %20 reduction in travel times and a %35 increase in traffic flow. Beyond just time saved in traffic, there's also a %15 decrease in fuel consumption rate. As a result of its implementation, approximately ₺700,000 worth of fuel is conserved annually. On average, each intersection benefits from a time-saving of approximately ₺1.7 billion per year.

Fuller et al. (2020) express DT are frequently used in the manufacturing industry to integrate data throughout physical and virtual machines, enabling simulation, evaluation and improvement of production processes. They also point out DT is able to offer current information on machine efficiency, identify struggles previously and increase reliability and performance. In addition, a number of industry leaders have used DT in everyday manufacturing and have applied appropriate patents for advances in technology in manufacturing (Pan et al., 2021a). Wang et al. (2017)

emphasize the importance of human-robot collaboration since it is very useful in industrial production and creates a safe and optimized production environment especially in assembly tasks. Collaboration between humans and robots may be observed in a variety of ways such as guiding the robot with 3D bare hand gestures and helping humans with physical tasks. According to them, DT is a virtual model of a production unit used for monitoring, analyzing, planning and control. It interacts with the real world by receiving real time sensor data and influencing the physical environment via robotics. They indicate this technology has the potential to be a valuable tool for continuous process assessment, improvement and engineering support during process changes.

DT technology offers a wide range of uses in the healthcare sector (Erol et al., 2020; Akanmu et al., 2021). Akanmu et al. (2021) point out, in healthcare, DT are frequently applied to simulate environments that are adapted to the needs of researchers, doctors, hospitals and healthcare providers. DT might be adopted to analyze the human body in real time, simulate the effects of medications and prepare for and execute surgeries (Fuller et al., 2020). Erol et al. (2020) mention it allows the creation of virtual copies of patients, leading to personalized diagnosis, treatment, and monitoring. Thus, DT can help hospitals optimize resource allocation and streamline processes. They also discuss that DT enables continuous monitoring of vital signs, providing valuable health information in the pharmaceutical industry when integrated with wearable devices. Furthermore they state, DT plays a significant role in developing personalized medicine and enhancing production efficiency. Moreover, they hold promise for improving organ transplantation outcomes and expediting vaccine and medicine development.

Additionally DT has various applications in smart cities; however, the studies primarily focused on the following areas: infrastructure management, urban planning and design, maintenance management and services (Lu et al., 2020a; Shahat et al., 2021). Lu et al. (2020a) express DT can be used to manage various aspects of city infrastructure, such as transportation systems, water and energy networks and waste management. Actual time data can be collected and analyzed to optimize their performance, detect anomalies and improve maintenance and resource allocation by creating a virtual replica of these systems. Furthermore they indicate that during the urban planning and design phase, DT plays a role by modeling various situations and assessing how they affect the city. Additionally they show DT has the potential to enhance citizen services and participation by offering individualized insights and suggestions. As researchers highlight, by integrating data from transportation systems, weather forecasts, and event calendars, DT provides public transport updates, suggests personalized activities, and enables interactive communication between residents and city officials. Moreover Austin et al. (2020) give an example of a data driven municipal operations center in Rio de Janeiro, Brazil, which collects live information from 30 companies, such as emergency, transit, utility, and security services, into one place. A team of 180 data operators oversees these records, keeping an eye on and responding to environmental and urban events. In another study, Kim and Ham (2020) collected image data via drones and created a DT and investigated the physical damage from the environment to the utility poles. Thus, with the data and information they obtained from research, they applied improvements regarding the positions and angles of the utility poles which is for better smart city applications. Fuller et al. (2020) state DT in smart cities can optimize energy consumption, improve infrastructure management, and enhance urban planning. They enable actual time analysis of data from various sources, such as sensors and IoT devices, to monitor and optimize the performance of city infrastructure, including transportation systems, utilities and public services. They further highlight that DT can help city planners make informed decisions, improve efficiency and enhance the overall quality of life in smart cities by simulating and analyzing different scenarios. Therefore they demonstrate, DT can be used for city wide simulations and monitoring, including areas like traffic management and renewable energy. DT in smart cities provide living analysis, simulation and prediction based on accurate analytics, contributing to more efficient and sustainable urban environments. (Fuller et al., 2020; Lu et al., 2020a; Kim et al., 2022)

In the aerospace industry, DT is utilized for upcoming NASA vehicles. They combine highly accurate simulations with integrated vehicle health management systems, maintenance records and past data to guarantee safety and dependability (Glaessgen and Stargel 2012).

2.1.3 Architectural and construction applications of digital twin

Construction sector, with its large labor force and GDP contribution, is a vital industry for all economies having an average contribution of %9 to national economies (Ellul et al., 2024; Nguyen and Adhikari, 2023). However, Arowoiya et al. (2023) highlight, the construction industry experiences various challenges such as low productivity, insufficient communication, limited technological advancement, inadequate project performance and low innovation. Moreover, despite the availability of technologies aimed at enhancing productivity and performance, the construction sector is reported to be slow in adopting innovative technologies compared to other industries (Hasan et al., 2018). With the rising need for greater efficiency and competitiveness in construction, the adoption of DT solutions is becoming increasingly common (Moshood et al., 2024). DT concepts are significant in the architecture, engineering, construction, and facility management (AEC/FM) sectors (Lu et al., 2020b). DT helps reduce the long-term impacts of buildings and makes the construction process more efficient (Boje et al., 2020). Furthermore, there are numerous applications for DT technology in the construction and architectural industries, and the field of architecture can greatly benefit from its utilization (Lu et al., 2020a; Wang et al., 2022). A review of the literature revealed a wide range of architectural applications of DT technology. These are include design visualization and simulation (Lu et al., 2020a; Wang et al., 2022), indoor environmental monitoring and optimization (Opoku et al., 2024; Hu et al., 2023; Khajavi et al., 2019), and energy performance and sustainability analysis (Zhang et al., 2022; Lu et al., 2020a; Debrah et al., 2022). Additionally, integrated technologies for performance forecasting (Almusaed & Yitmen, 2023; Elfarri et al., 2022; Boje et al., 2020), real time monitoring and facility management (Sun et al., 2022; Lu et al., 2020b), and anomaly detection (Lu et al., 2020b; Hosamo et al., 2022) are commonly discussed applications. Furthermore, reducing construction errors and enhancing on site coordination (Wang et al., 2022; Deria et al., 2022; Boje et al., 2020), enabling human robot collaboration in construction tasks (Wang et al., 2021), and managing lifecycle data (Opoku et al., 2024; Lu et al., 2020b) are also among the notable areas of implementation in architectural practice. Lu et al. (2020a) emphasize that the operation and maintenance phase, which lasts the longest in the property's life cycle, has received less attention in studies, so the key initial step for efficiently managing and sustaining buildings is to establish a well-structured framework, supported by real world examples, for creating a DT. But in contrast, Almatared et al. (2022) claim that the operation and maintenance phases of the building's life cycle are where DT technologies are most commonly used particularly. The reason for these two different opinions might be the increasing demand for research on this subject in the last 2 years. Applications and advantages of DT for establishing smart construction services are numerous such as enhanced site sensing, real time data visualization and increased application of AI (Bosch-Sijtsema et al., 2021; Wang et al., 2021). Some researchers have analyzed the architectural applications of DT focusing on indoor conditions whereas others discuss energy efficiency in terms of sustainability, site sensing and human robot collaboration. Boje et al. (2020) mention that DT offers a significant enhancement in site sensing. Furthermore they indicate DT offers real time data visualization, which allows for the careful monitoring and control of assets throughout their entire lifespan. Lastly, the study adds using AI into DT can enhance human involvement in negotiation heavy construction processes. Similarly Almusaed and Yitmen (2023) highlight AI simulators and DT are used in smart building design ideas to improve building performance and client satisfaction. The models simulate various design options and forecast their effects on building efficiency, comfort and security using data about structure use, architectural form and functions, plus environmental factors. The models are able to evaluate several design possibilities, identify any problems and improve building operations and satisfaction for users.

Wang et al. (2022) express buildings using DT programs have immediate access to constructed models. This means that they will be actual time connected, current status work tracking is possible for companies. They mention the use of DT in construction has the potential to address typical issues in the construction process, such as minimizing errors and redundancies by providing real time information updates to construction sites. Furthermore as Sun et al. (2022) indicate, DT can make it simple to access elements for managing building operations, allowing for improved efficiency of building operations and the early identification of emergency situations. Also by converting management system choices into practical actions, they may control the operation in the real world. In addition they express that the information stored digitally plays a crucial role in making building operations more efficient and provides a system for managing operations more effectively.

As Lu et al. (2020a) state DT finds application in the design and construction stages of building projects. They offer architects a digital representation of the structure, enabling them to visualize the design, spot potential problems and implement required modifications before starting construction. The study shows DT is also valuable during a building's operational and maintenance phase. Researchers supply real time information on the building's performance, assisting facility managers in overseeing its state, forecasting maintenance requirements and optimizing operational processes. Moreover they state that the DT can play a role in promoting sustainability in architecture through giving information on a building's energy consumption, water use and waste production. This data helps architects and building owners in developing plans to reduce the building's ecological footprint. As Debrah et al. (2022) reveal, sustainability, involving the effective use of resources, is extremely problematic for the AEC industry because construction activity generates the majority of global energy consumption (36%) and carbon emissions (37%).

Wang et al. (2021) designed a task for DT application where participants collaborated with a robot to install drywall panels. The case study involved vertically installing four panels on a wall frame, with participants choosing the order and type of drywall for each task. In conclusion, they highlight that DT provides a virtual representation of the real environment, integrating crucial real world data to facilitate construction tasks and enable instant changes and revisions. The research concludes that human-robot collaboration reduces human error and enhances the benefits of technology as Deria et al. (2022) emphasize the importance of reducing human errors by using DT.

Similarly Khajavi et al. (2019) gather, examine and use over 25,000 sensor measurement examples to develop and confirm a restricted DT of a facade piece for an office building. They conducted the study to illustrate the implementation strategy and emphasize the advantages of the DT. In the experiment, after processing the light sensor data, software was used to represent the current condition of facade brightness. Consequently, they express that the lighting system's daily energy consumption can be significantly reduced. In the study, they concentrated on applications of a DT aimed at reducing maintenance costs, enhancing tenants' comfort and decreasing the overall management and operational expenses of a building. Furthermore they mention the DT equipped with sensors that measure air quality, temperature and relative humidity can provide the necessary data for implementing an air conditioning system in indoor spaces. Likewise Zhang et al. (2022) state measurement and management of energy performance as the most important application factor for buildings and how DT can help us accomplish control over energy efficiency. Energy analysis for buildings in the design stage and implementing energy management in close to real time during the operational phase are examples. Moreover, they mention that the DT in the workplace can facilitate the best possible design and use of office space through the use of performance and health information from people inside. The result can improve user happiness and provide owners more control over the workspace.

Opoku et al. (2024) focus on creating DT to track interior conditions in a university library, campus of Western Sydney University. To do this, technologies for the IoT and BIM integrated to produce a semiotic representation of the internal parameters of the library. Improving air quality, the lighting and temperature control inside the building is the goal. The paper discusses the difficulties in incorporating current time tools for data collecting and graphical representation in the construction sector. Hu et al. (2023) particularly intend to improve the automation and accuracy of preserving indoor air quality by developing a parallel deep learning approach for failure forecasting and a system of prediction facilitated by DT. The goal of the project is to increase comfort for tenants, reduce hazards and quicker repair processes in building settings while filling the research gap in predicting failures for interior conditions.

In a study conducted by Elfarri et al. (2022), they utilize data derived from a contemporary residence, encompassing diverse parameters associated with the home's surroundings and functions. Afterward, machine learning models are developed and trained with this data to construct predictive models capable of anticipating the future states of the house. The evaluation of these models focuses on performance metrics, including accuracy in predicting various conditions within the residential environment.

Besides Lu et al. (2020b) point out efficient asset management is crucial for ensuring the optimal performance and serviceability of buildings. Despite this importance, there is a shortage of effective strategies and comprehensive methods for handling assets and their data in a way that facilitates the monitoring, detection, recording and communication of operation and maintenance issues. This study introduces a DT-enabled anomaly detection system to improve asset monitoring in daily operations and maintenance. The heating, ventilation and air conditioning (HVAC) system of the Institute for Manufacturing building at the University of Cambridge serves as a case study. To demonstrate the DT's capabilities in data integration, anomaly detection and visualization, the system monitors the building's centrifugal pumps. Similarly Hosamo et al. (2022) focus on the HVAC system of the building and examine its operation with DT. Although the researchers work on a similar topic, they approach it with different methodologies. Hosamo et al. (2022) adopt predictive maintenance technology with BIM, IoT and ML techniques to monitor errors whereas Lu et al. (2020b) employ the Bayesian online change point detection methodology for anomaly detection.

A bibliographic analysis was conducted to understand the research trends and status of the DT concept in the literature. Research related to DT and the construction sector was gathered from the Scopus database. All types of documents, including conference papers, articles, reviews, book chapters, books and conference reviews were considered to capture the perspectives of researchers. No time constraints were imposed on accessing information in the literature, but the focus of the paper is on research conducted in English. The advanced search engine on Scopus was utilized, with filtering based on Title-Abstract-Keywords. The search code employed was TITLE-ABS-KEY ("digital twin") AND TITLE-ABS-KEY ("construction project" OR "construction industry" OR "construction sector") AND (LIMIT-TO (LANGUAGE, "English")). A total of 340 publications were identified during the search. Subsequently, the publication data from the Scopus database for the current search was exported as a CSV file for bibliometric mapping using VOSviewer software. In the Scopus search, information related to a total of 340 publications was obtained and Figure 2.4 illustrates the distribution of these documents across different years. The earliest data available in Scopus dates back to 2018. The chart depicts a steady increase in publications since 2018, with a notable rise in 2020. Although the publication count has been doubling on average each year until 2022, the publication counts for 2022 and 2023 are very close to each other. This result may mean that due to the publication count reaching a certain point, the number of publications related to the topic may not show a steep increase in the coming years on the graph; this might indicate a saturation level. It's important to note that the analysis concluded in the early months of 2024, and the statistics for that year may not fully represent the current circumstances. Therefore, the apparent decline in the figure might not signify an actual reduction in numbers. Nevertheless, it can be inferred that interest in the DT concept experienced a significant expansion between 2018 and 2023.

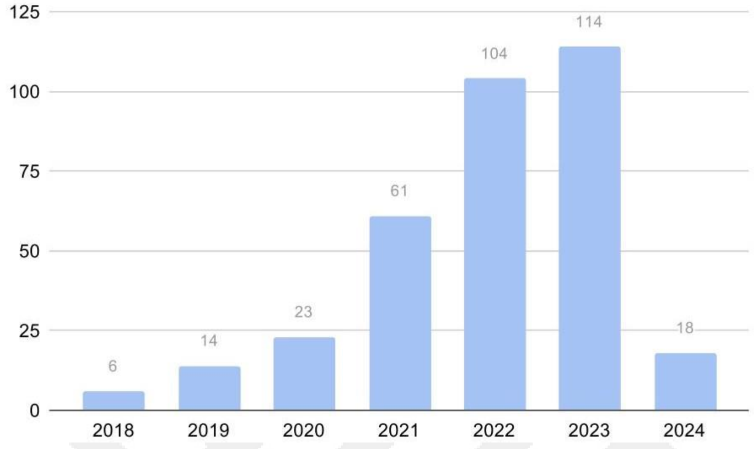

Figure 2.4 : Amount of publications for DT in AEC during 2018-2024.

Figure 2.5 shows the document type distribution. Among the 340 papers addressing digital twin applications in the construction industry, articles and conference papers constitute approximately 82%. Reviews (10.9%) and conference reviews (4.1%) come next, with 37 and 14 publications, respectively. Books (0.9%) and book chapters (2.6%) are the least preferred types in the table.

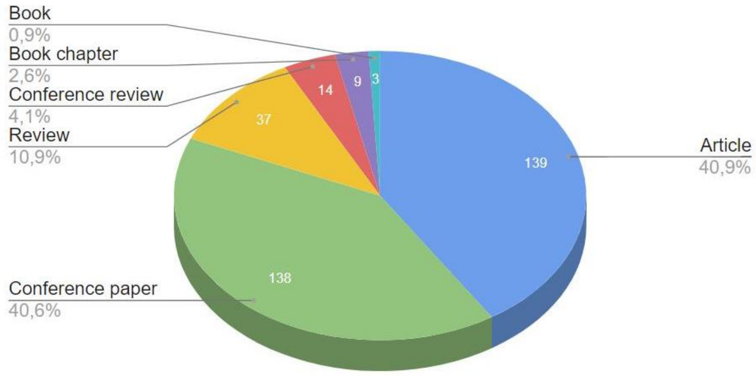

Figure 2.5 : Type of publications.

For citation analysis, VOSviewer was employed to analyze citations in AEC industry documents related to DT. According to Scopus, 5 major contributors in this area are identified and listed in Table 2.1. These are: Boje et al. (2020), Opoku et al. (2021), Pan et al. (2021a), Lee et al. (2021), Sepasgozar (2021).

Table 2.1 : The most cited publications on DT in construction industry.

No	Author	Title	Citation	Research Focus
1	Boje et al. (2020)	Towards a semantic construction digital twin: Directions for future research	476	Authors emphasize the necessity of a construction digital twin (CDT), identifies capabilities and highlight key research issues in the domain. Also they address BIM's weaknesses and limitations.
2	Opoku et al. (2021)	Digital twin application in the construction indusrty: A literature review	214	The paper examines the DT idea, growth of the concept, essential technologies and six application area in the lifecycle stages of a project and implementation in the construction industry.
3	Pan et al. (2021)	A BIM-data mining integrated digital twin framework for advanced project management	212	The study presents DT structure that incorporates data mining, IoT and BIM to enhance intelligent construction project management. Moreover future perspectives on construction through the application of DT and AI are given in the paper.
4	Lee et al. (2021)	Integrated digital twin and blockchain framework to support accountable information sharing in construction projects	178	The paper aims to establish an integrated framework that combines DT technology with blockchain for improved data communication and enhanced information sharing among construction project stakeholders.
5	Sepasgozar (2021)	Differentiating digital twin from digital shadow: Elucidating a paradigm shift to expedite a smart, sustainable built environment	129	Emphasizing its importance in implementing Industry 4.0 to differentiate DT from other digital modeling practices. It also highlights integrating DT with blockchain and deep learning, demonstrating benefits in improving efficiency.

Among these publications, the work of Opoku et al. (2021) is featured in the Journal of Building Engineering, the contribution of Sepasgozar (2021) is found in Building, whereas the remaining ones are published in Automation in Construction. The documents commonly focus on discussing the influence of DT on productivity and efficiency, as well as the potential of collaboration with other emerging technologies in shaping the future of the construction sector. We may determine the widespread use of particular themes and the focus of research by examining the co-occurrence data of author keywords in papers. Utilizing VOSviewer, we generated a co-occurrence network of author keywords, where the size of keywords reflects their popularity, colors distinguish clusters, and the distance indicates similarity. Furthermore, the connections between terms indicate relationships inside the DT and the construction industry. With 2 being the minimum number of keyword occurrences,155 keywords out of 868 meet this criterion. Figure 2.6 displays a bibliometric map illustrating the co-occurrence of author keywords.

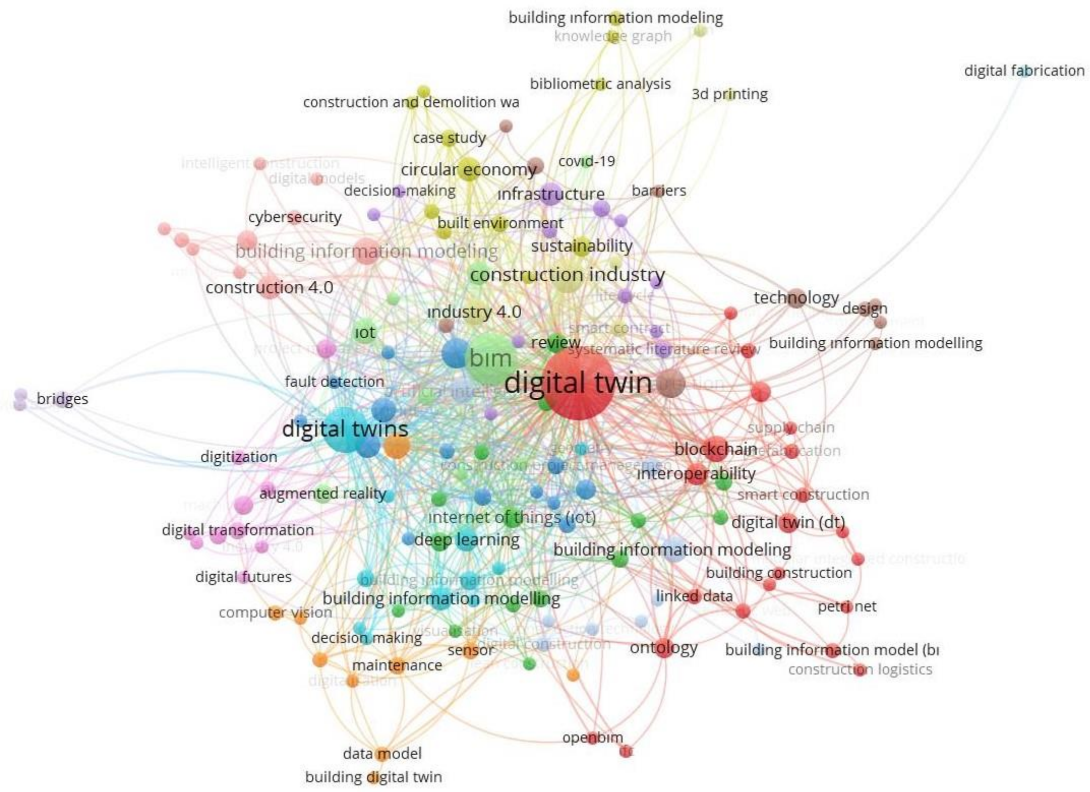

Figure 2.6 : Bibliometric map of author keywords co-occurrence network.

Based on the analysis, the term digital twin emerges as the most frequent keyword, appearing 132 times, in cluster 1, indicating a significant association with other relevant concepts. Following closely is BIM, the second most common keyword, occurring 57 times and placed in cluster 11. The third, digital twins, is part of cluster 6 with 41 occurrences. In this map, several terms that are associated with the computer and machinery industries are found in minor clusters, including cyber physical systems, fault detection, neural network, smart contract, petri net and more. According to the definition of the National Institute of Standards and Technology, cyber-physical systems involve the interaction of various components, including physical, digital, analog and human elements and are designed with integrated logic and physics to ensure effective functionality (NIST, 2024). International Business Machines defines a neural network as a model or machine learning program that mimics the way the human brain makes choices (IBM, 2024). Also a petri net tool is capable of being used to simulate the system, produce code, examine its performance, and verify the model (Thong, 2015). This occurrence may be attributed to the direct impact of advancements in computer science and technology on the application of DT in the construction sector. Moreover, research on DT spans across interdisciplinary areas, including engineering, information science, and computing. Nodes of smaller size indicate a less frequent discussion in academic publications compared to larger nodes. Nevertheless, if a topic is a recent development, it may have future growth potential. To gain insights into this matter, it is necessary to closely examine the historical development of keywords. In response to this goal, Figure 2.7 was generated by integrating historical data into the analysis.

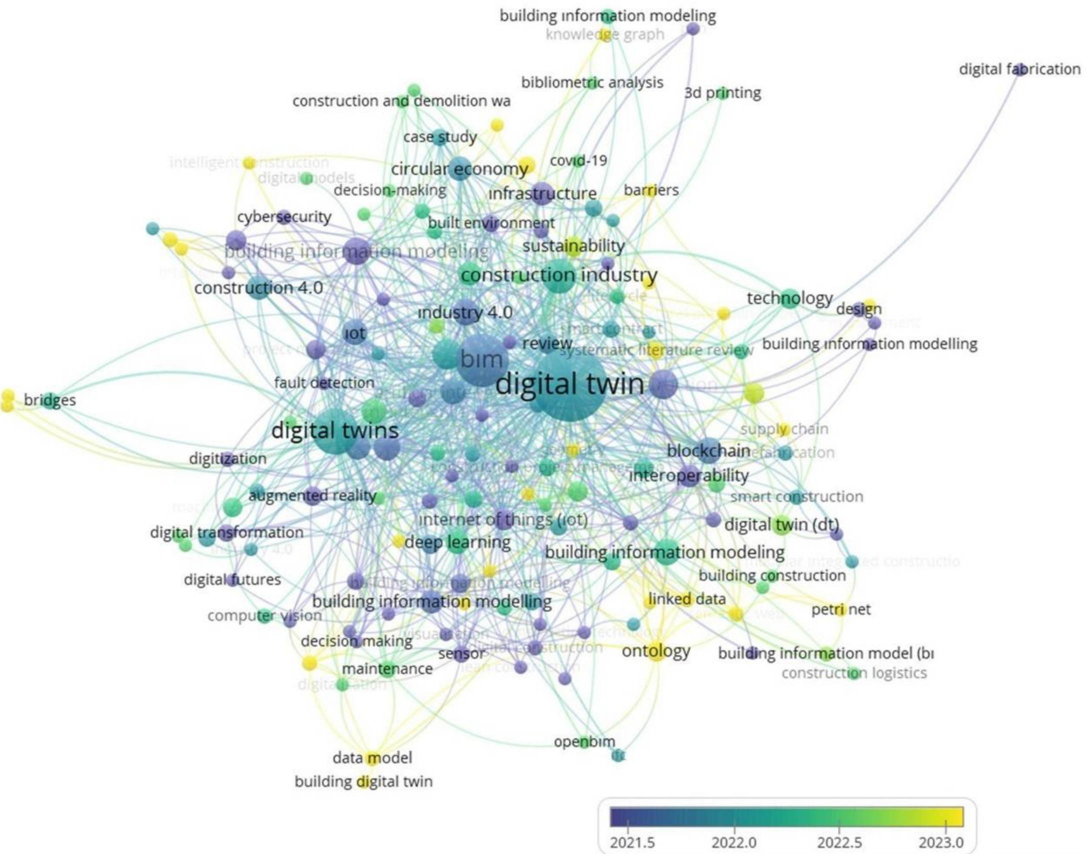

Figure 2.7 : Bibliometric map of author keywords co-occurrence overlay.

The addition of a time option to the overlay visualization map causes the colors to change, but the screen, point size and clusters stay the same (McAllister et al., 2021).

The cluster colors transition from blue to yellow as the years approach the present. Examining the keywords published annually as an overlay, terms such as digital twin, BIM, construction industry, internet of things and industry 4.0 stand out as being crucial in the field; they are frequently used in academic papers and indicate the largest clusters. Furthermore, these terms are predominantly shaded in either green or blue, signifying their extended usage by researchers. Notably, within the notable blue clusters, the most significant ones include BIM, construction, big data, blockchain and facility management each featuring in 57, 14, 11, 11, and 10 documents, respectively. On the other hand, within the expansive green clusters, aside from the terms digital twin, BIM and construction industry, we find internet of things, artificial intelligence, virtual reality and deep learning noticeable each with 15, 10, 8, and 8 occurrences, respectively. Lastly, we note that greatest terms within the yellow cluster are predictive maintenance (9), sustainable construction (6), construction management (6) and ontology (6). Moreover, there are keywords that are primarily observed within the yellow clusters, which are highly specialized in the field of DT technology such as semantic web, industry foundation classes (IFC), intelligent construction, scan to BIM and automation. Recent research predominantly utilizes the keywords found in the yellow clusters. However, this does not guarantee their sustained relevance in the future. Future studies might reveal an expansion in their significance or they could remain relatively small. We can state that future modifications in their dimensions could occur. Moreover, according to the analysis, yellow, which is currently chosen keywords, refers to more specific topics compared to terms found in other colors. Table 2.2 has been created to enhance the distinction among the keywords found in the clusters shown in Figure 5. It clearly depicts the clusters, their colors and the keywords associated with each cluster in a list format. These 15 clusters were titled with DT to more accurately represent the application area of the construction sector. The first cluster, "DT and Construction," consists of 22 keywords, making it the group with the most keywords. Cluster 2, "DT & Technological Advancements" has 15 keywords. Cluster 3, "DT & Management" consists of 14 keywords. The top 3 clusters have the most keywords, followed by the clusters C4 (12), C5 (12), C6 (11), C7 (10), C8 (10), C9 (10), C11 (10), C12 (9), C13 (6), C14 (3) and C15 (1).

Table 2.2 : Clarification of the clusters.

No	Cluster Name	Colour	Keywords	Top 3 Keyword	Top 3 Occurences
1	DT & Construction	Red	blockchain, building construction, building information model (bim), construction logistics, cyber-physical system (cps), digital twin (dt), digital twin construction (dtc), ifc, interoperability, linked data, literature review, modular integrated construction (mic), ontology, openbim, petri net, prefabrication, semantic web, smart construction, structural equation modelling, supply chain, sustainable construction	Digital Twin Interoperability Ontology	132 7 6
2	DT & Technological advancements	Dark Green	artificial intelligent (ai), building information modeling (bim), building information modelling (bim), collaboration, construction safety, construction site, digital twins (dt), framework, industry foundation classes (ifc), internet of things (iot), lean construction, mixed reality, review, systematic literature review (slr), visulisation	Internet of things (iot) Review Construction safety	6 6 5
3	DT & Management	Dark Blue	building information model, construction management, construction project management, cyber- physical system, energy management, engineering project management, facility management, fault detection, internet of things, optimization, predictive maintanence, risk management, simulation, smart building	Internet of things Facility management Predictive maintanence	15 10 9

Table 2.2 (continued) : Clarification of the clusters.

No	Cluster Name	Colour	Keywords	Top 3	
				Keyword	Occurences
4	DT & Sustainability	Yellow	bibliometric analysis, building, building information modeling, built environment, case study, circular economy, consruction and demolition waste, construction sites, digitalization, knowledge graph, sustainability, waste minimization	Circular economy	9
				Sustainability	6
				Built environment	4
5	DT & Engineering	Purple	bridge, civil engineering, decision-making, digital maturity, infrastructure, inspection, life cycle, neural network, smart cities, survey, systematic literature review, wireless sensor network	Infrastructure	8
				Bridge	4
				Systematic literature review	4
6	DT & Decision making	Blue	building ınformation modelling, building information modelling, decision making, deep learning, digital twins, geometry, internet of things, occupational health and safety, safety management, scan-to-bım, scan-vs-bım	Digital twins	41
				Deep learnin	8
				Building ınformation modelling	8
7	DT & Big data	Orange	3d reconstruction, big data, building digital twin, computer vision, data model, digitalisation, maintenance, modeling, sensor, structural health monitoring	Big data	11
				Maintenance	4
				Sensor	4
8	DT & Automation	Brown	automation, barriers, building ınformation modelling (bım), construction, construction ındustry, construction sector, design, ınformation systems, management, technology	Construction	14
				Technology	6
				Construction ındustry	4

Table 2.2 (continued) : Clarification of the clusters.

No	Cluster Name	Colour	Keywords	Top 3 Keyword	Occurences
9	DT & Digitalization	Pink	aı, digital futures, digital transformation, digitization, energy efficiency, green buildings, industry 4.0, machine learning, productivity, project management	Project management	5
				Machine learning	5
				Digital transformation	4
10	DT & Cyber systems	Light Red	building information modeling, construction 4.0, cyber- phsical systems, cybersecurity, digital models, ıntelligent buildings, intelligent constructin, off-site construction, scientometric analysis, smart buildings	Building information modeling	12
				Construction 4.0	9
				Cyber-phsical systems	6
11	DT & Virtual design	Green	arhitecture, augmented reality, bım, covid-19, engineering, gıs, ıot, smart city, virtual design and construction, virtual reality	Bım	57
				Virtual design and construction	11
				Iot	10
12	DT & Innovation	Light Blue	artificial intelligence, building information modeling (bım), construction technology, digital construction, digital technologies, ınnovation, modular construction, offsite construction, process mining	Building information modeling (bım)	11
				Artificial intelligence	10
				Modular construction	5

Table 2.2 (continued) : Clarification of the clusters.

No	Cluster Name	Colour	Keywords	Top 3 Keyword	Top 3 Occurences
13	DT & Industry 4.0	Light Yellow	3d printing, construction industry, decentralization, ındustry 4.0, plm, smart contract	Construction industry	21
				Industry 4.0	11
				Smart contract	4
14	DT & Prototyping	Lilac	bridges, prototyping, synthetic faır data	Bridges	4
				Prototyping	2
				Synthetic faır data	2
15	DT & Fabrication	Grey	digital fabrication	Digital fabrication	2

Keywords like petri net, linked data, openBIM and structural equation modeling as well as terms such as energy management, predictive maintenance, simulation and risk management are present in these clusters, showcasing a notable expertise in the relevant fields. These keywords are seen in the yellow cluster in Figure 6, further demonstrating how studies have become more specialized and in-depth recently. Table 2.3 presents the numerical data about the author keywords in the map. Within the table, the most frequently used top 20 keywords are clearly visible, which the map created with VOSviewer might not be very obvious and easy to distinguish. Similar or synonymous words have been included in the study to demonstrate how the words appear in different contexts and forms in research papers. The results simply indicate the research trends of DT in the construction sector.

Table 2.3 : Top Keywords in DT for the AEC Sector.

No	Keywords	Occurences	Links	Total Link Strenght	Avg. Pub. Year
1	Digital twin	132	116	331	2021.96
2	BIM	57	68	152	2021.72
3	Digital twins	41	68	111	2022.05
4	Construction industry	21	41	69	2022.19
5	Internet of things	15	35	56	2022.07
6	Construction	14	28	45	2021.57
7	Building information modeling	12	26	35	2021.25
8	Big data	11	33	49	2021.64
9	Blockchain	11	24	43	2021.73
10	Industry 4.0	11	22	42	2021.64
11	Building information modeling	11	17	22	2022.27
12	IoT	10	21	38	2021.70
13	Artificial intelligence	10	22	34	2021.80
14	Facility management	10	19	31	2021.70
15	Construction 4.0	9	17	25	2021.89
16	Predictive Maintenance	9	14	24	2022.44
17	Circular economy	9	18	22	2021.89
18	Building information modelling	8	24	29	2021.62
19	Deep learning	8	22	27	2022.38
20	Virtual reality	8	15	24	2022.38

Although BIM and related topics continue to maintain their prominence in the literature, we can observe the emergence of AI and related subjects such as IoT, predictive maintenance, deep learning and virtual reality in recent research trends. With the increased presence of these terms related to various technologies in the building sector, positive effects on productivity and efficiency are observed. This bibliometric analysis provides the yearly distribution and classification of publications, a co-occurrence network of author keywords, and a list of the top 20 terms connected to DT in the construction industry in order to identify current research trends. The analysis used research article keywords to examine DT's potential. At various phases of the building life cycle, these terms may have different purposes in the construction industry. In the design stage, terms like BIM and risk management may be the most popular, but in operation and maintenance, cyber-physical systems and facility management could be more important. The construction phase might be impacted by IoT, sensors, smart contracts, optimization and simulation, while the end of life phase could be influenced by circular economy and waste minimization. As Komar et al. (2024) indicate, these emerging terms might show that research on construction is becoming more specialized in the topic. Their presence could emphasize its strategic significance in the AEC sector and ability to influence future developments in the sector.

2.1.4 Digital twin throughout the building life cycle

Many phases of the building lifecycle have been the subject of research examining the potential and preliminary scenarios for the implementation of DT (Chen et al., 2024). The potential of the idea of DT to improve building lifecycle management has been highlighted (Khajavi et al., 2019). Akanmu et al. (2021) discuss, in the building sector, DT enhances lifecycle management from planning to operations by providing a digital model that supports process optimization and decision making. Likewise as Boje et al. (2023) indicate the main objective of the DT is to assist in improving the management of the structures or procedures associated with them. However, they further state that there are various applications of DT related to different stages of the life cycle of a building in the construction sector. They claim the DT for a construction asset is intended to span its entire lifecycle; nevertheless, there exists a significant contrast in the dynamics between the construction and operational phases. As a result, they mention distinct implementations are required for the DT during the construction phase as opposed to the operational stage. They define the goal of a DT as a construction strategy to build things more efficiently. Also they highlight that the DT of the building starts to form during the construction phase but attains more advanced levels of development during the operational stage. Akanmu et al. (2021) show that DT is essential for optimizing project lifecycle steps, particularly in the stages of design, construction, operations and maintenance. Additionally, Menegon and Filho (2022) state in the planning and management phase, the incorporation of new technologies typically brings about a significant transformation with the construction stage following it. In addition to all, Khajavi et al. (2019) discuss that implementing a DT for building life cycle management offers various benefits including enhanced construction efficiency, predictive maintenance, improved resource efficiency, increased tenants' comfort and optimized building design. Moreover, they claim DT can provide valuable insights for designing future buildings based on identified flaws and improvement areas during the use phase. Thus, architects can utilize a DT to enhance the performance of upcoming buildings during modifications, renovations and when planning future constructions. Also they state a significant point that DT might play a role in reducing maintenance costs and decreasing the overall management and operational expenses of a building. Figure 2.8 conceptually shows the life cycle of a building, the roles of DT and the usage phases of different types of DT.

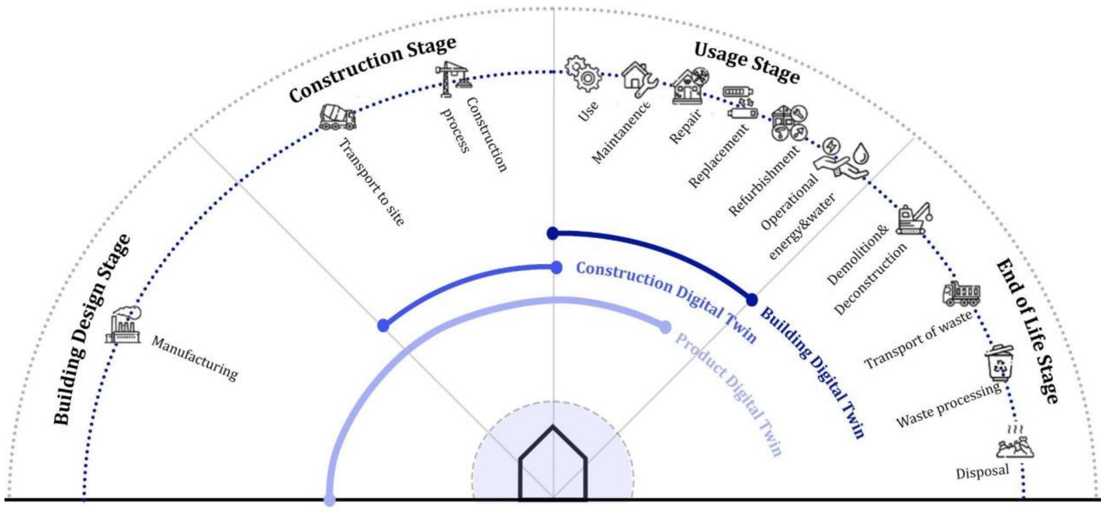

Figure 2.8 : The framework diagram illustrating the relationship between digital twins and the building life cycle adapted from Boje et al. (2023).

Firstly, the product DT might be overseen and controlled apart from the location or structure, and it can also give its maker input at a different point in the product's life cycle. Advanced products may include built-in sensing and/or actuation capabilities. However, this situation is not yet widespread in the sector. Secondly, the construction digital twin (CDT) is responsible for controlling the progress and ongoing activities at the construction site. Just-in-time delivery, the use of equipment on site, work environment like pollution, weather and worker risks, as well as working conditions including hours worked and contact with hazards, can all be monitored by the CDT. The costs are reviewed and updated to account for the most recent occurrences. Lastly, building DT uses sensing technology to observe indoor conditions similarly to the CDT, but primarily an emphasis on building tenants. Predictions could be made for conditions at work, the effects on people's health and security. Expenses to the property owner and residents may be computed more precisely when considering environmental effects. For the end of life stages in actuality, the building DT's function is over there, but the life cycle information it has collected can be saved and used as a knowledge base for upcoming projects, uses, and studies (Chen et al., 2024; Boje et al., 2023; Yoon et al., 2023; Khajavi et al., 2019).

In brief, throughout the lifespan of a project, DT can be extremely valuable because they facilitate process permits, automate recording, control as-designed and as-built details, optimize scheduling of resources, enhance logistics and security tracking, enable predictive maintenance, guarantee assurance of quality and encourage legality (Teisserenc and Sepasgozar, 2021).

2.1.5 Applications of digital twin in the construction phase

Opoku et al. (2021) assert in the building life cycle, the construction phase is extremely important because it's the stage that creates the final output. They state construction sector activities are effectively handled with the help of DT. In a different way Yang et al. (2024) emphasize the building stage of a project's lifespan includes not only converting designs and plans into a real building but also performing at the highest levels of resource, budget and time management to guarantee the project's successful completion. Additionally, they point out that the project's safety, quality, time and cost effectiveness will all be directly impacted by the construction stage's performance. Boje et al. (2020) point out adoption of construction DT could revolutionize the construction industry. This would enable cost reductions, greater ecological responsibility and improved lifecycle management. Plus, DT should access all project data, understand the big picture and provide useful information. Almatared et al. (2022) propose integrating DT in construction stages by using the numerical results. In the construction stage, by combining innovations such as BIM, drone surveys and laser scanning, a DT of the job site is created, enabling efficient site management, scenario estimation and decision making through the integration of IoT devices with the BIM model (Piras et al., 2024). DT might be utilized to support construction monitoring and management, involving progress, security, quality, workforce, equipment and materials by applying it to surrounding environments, current projects and even partially constructed buildings (Jiang et al., 2021; Yang et al., 2024). Although there are numerous applications and benefits of DT in the construction stage as CDT; the literature primarily focuses on following areas: workforce oversight, material and equipment management, site monitoring, optimization of time and cost, enhanced decision making processes, integration with emerging technologies and comprehensive participation. The applications and details are presented in Table 2.4.

Table 2.4 : Key applications of DT in the construction phase.

Key Application Area	Implementation Purposes	References
Workforce Oversight	Reducing human errors Gathering health data from sensors Fixing body posture Labor location detect	Ellul et al. (2024), Wu et al. (2024), Deria et al. (2022), Hu et al. (2022), Wang et al. (2021), Jiang et al. (2021)
Material and Equipment Management	Waste management Lojistic and supply chain Location detect Optimization of workflow Situation monitoring	Arsecularatne et al. (2024), Yang et al. (2024), Boje et al. (2023), Hu et al. (2022), Deria et al. (2022), Jiang et al. (2021), Akanmu and Anumba, (2015)

Table 2.4 (continued) : Key applications of DT in the construction phase.

Key Application Area	Implementation Purposes	References
Site Monitoring	Real-time data collection Control of machines Dynamic virtual illustration Safety and risk management	Moshood et al. (2024), Yang et al. (2024), Arowoiya et al. (2023), Boje et al. (2023), Hosamo et al. (2022), Wang et al. (2022)
Optimization of Time and Cost	Enhancement via DT-integrated technologies	Salih and El-adaway (2024), Lauria and Azzalin (2024), Piras et al. (2024), Yang et al. (2024), Jiang et al. (2021)
Enhanced Decision Making Processes	Upgrade current decision-making strategies Employing greater data and innovative technologies into process	Lauria and Azzalin (2024), Moshood et al. (2024), Arseculartne et al. (2024), Wang et al. (2022), Bakhshi et al. (2024), Wang et al. (2021)
Integration With Emerging Technologies	Ability to incorporate (AI, IoT, ML, VR, AR, DL, CPS etc.)	Piras et al. (2024), Yang et al. (2024), Wu et al. (2024), Hu et al. (2022), Begić et al. (2022), Wang et al. (2021), Boje et al. (2020)
Comprehensive Participation	The equal involvement of various stakeholders	Zhang et al. (2024), Bakhshi et al. (2024), Arowoiya et al. (2023), Nguyen and Adhikari (2023), Jiang et al. (2021)

2.1.5.1 Workforce oversight

The DT approach in the construction stage aims to prevent losses from delays, hazards and rework due to human errors while reducing unproductive time and reliance on manual processes (Deria et al., 2022; Hu et al., 2022). Wang et al. (2021) express in the DT system, labor can be rescued from repeated and physically exhausting jobs by working with robotics. In addition it decreases the necessity of being actually present on possibly dangerous building locations for humans. Ellul et al. (2024) investigate the use of wearable technology for real time labor location tracking in order to improve jobsite security by anticipating hazards and detecting incidents narrowly. They claim human centered DT are crucial for the security of workers and it has a lot of promise for better safety and health standards in building projects. Also in their study Jiang et al. (2021) explain a DT framework created to understand labor movements in dynamic building environments by gathering real time data and analyzing worker motions with a BIM model. Furthermore, they mention a posture education platform that was created to assist employees in practicing jobs with lower hazards from ergonomics utilizing wearable technology, machine learning and virtual reality. Wu et al. (2024) discuss that real time danger identification is possible by combining DT with AR to produce 3D representations of hazard sources, AR alerts, human locations and line of sight directions. This enhances the awareness of circumstances and safety of the workers on the job site. Moreover DT keeps records of circumstances at work, including the total amount of hours spent on activities and the risks encountered (Boje et al., 2023).

2.1.5.2 Material and Equipment Management

Boje et al. (2023) indicate further services, such as monitoring and transport optimization to guarantee on-time delivery, are made possible via DT. Also the CDT can oversee on-site equipment usage and working conditions, such as pollution, weather and worker safety hazards. It calculates the impact on human health and greenhouse gases produced by machines. By increasing efficiency in energy use and decreasing waste, DT improves sustainability by facilitating continuous monitoring and optimization (Arsecularatne et al., 2024; Yang et al., 2024; Hu et al., 2022). Similarly Deria et al. (2022) state in order to reduce resource waste, the DT system uses current sensor information from building sites to improve resource allocation. Also they indicate the traditional methods in the construction operations lead to delays and inefficiencies. However, the goal of integrating AI and DT systems is to minimize those human mistakes by automatically allocating resources and rationalizing workflow cycles. Jiang et al. (2021) state for secure, precise and effective construction, DT can track, operate and regulate machines. Also DT assists contractors in keeping an eye on material requirements and informing suppliers as needed. Additionally, it can provide a lean theory-aligned workflow for managing building supplies. The current time visual data can also assist in conducting various planning simulations, such as equipment allocation plans, temporary logistics and construction tasks (Boje et al., 2020). Akanmu and Anumba, (2015) discuss that material monitoring and activity observation by combining digital representations with real construction, might enhance on-site safety and efficiency. They suggest sensors to track item location, delivering geographical coordinates and status reports. Predicting skills of DT, which are powered by location data to solve a variety of issues, present enormous promise for construction scheduling, including elimination of waste, procurement and the construction workflow (Ellul et al., 2024).

2.1.5.3 Site monitoring

DT are essential throughout the construction phase because it provides real time monitoring and synchronization with the simulation (Wang et al., 2022; Boje et al., 2023; Akanmu and Anumba, 2015). DT enables rapid site issue resolution and actual time viewing of construction site conditions (Hu et al., 2022; Akanmu and Anumba, 2015). Boje et al. (2020) discuss that while current methods rely on periodic laser scans and manual updates from people, DT utilizes real time sensor data to offer more precise and timely information. This enhances the accuracy of DT in representing the construction site's status. Methods such as AI and visualization could be employed in site monitoring to observe specific progress using object-based methods so that as constructed photos and as planned simulation can be compared (Jiang et al., 2021). Similarly Boje et al. (2023) state the Construction Digital Twin (CDT) is essential for ensuring an efficient construction process by aligning the as-designed models with real time project execution. Thus DT might prevent undesirable situations that cause delays (Hosamo et al., 2022). By integrating DT with industry 4.0 technology, an accurate digital duplicate of the site is produced, allowing efficient control and continuous tracking throughout the project lifespan thereby enhancing safety measures (Moshood et al., 2024). Regarding the construction phase, Arowoiya et al. (2023) state that implementing the DT in the construction process, in terms of safety, will help create a less hazardous atmosphere and increase productivity by giving laborers access to real time information and visualize what's happening in the construction area. Yang et al. (2024) state the proper simulation, observing and evaluation of building situations at various periods are made possible by DT. During the building stage, DT can be utilized to take pictures or videos of the actual site by integrating AR and VR technologies with sensors to provide remote instruction, safety monitoring, and risk alert. Also the existing state of traditional safety monitoring methods can be modified by this technology.

2.1.5.4 Optimization of time and cost

DT is one of the greatest factors influencing reduction of expenses (Salih and El-adaway, 2024). For time and cost management, DT measures the amount of the task finished as intended and evaluates its completion status (Jiang et al., 2021). Boje et al. (2020) assert AI serves as a bridge between various planning systems and different datasets, raising the integration of information at all levels. Additionally, AI contributes to optimizing construction scheduling and logistics, leading to increased construction productivity. By incorporating schedule and cost factors, a deeper link between the design and construction phases is established, while lowering the possibility of additional expenses brought on by rework (Yang et al., 2024). DT may enable process optimization for the building industry, improving quality and lowering expenses (Lauria and Azzalin, 2024). Salih and El-adaway (2024) propose a decision-support model to help generate both cost and time progress or reductions associated with the use of construction innovations. Therefore, by more precisely forecasting project performance outcomes, the model enhances decision making on the implementation of technology for building. Eventually, it maximizes the success of construction projects. Piras et al. (2024) suggest the digital management methodology that is a strategy method incorporating digital technologies including DT, BIM, IoT and AI in order to enhance building steps and solve problems resulting from traditional time and cost management techniques such as work breakdown structure. It enables graphical identification of construction activities, real time progress tracking, insight into resource allocation. Via DT in this stage, the construction process can be accurately analyzed, human resource utilization monitored, cash flow trends reviewed to adjust the project budget, and quality and timelines ensured.

2.1.5.5 Enhanced decision making processes

The integration of DT with Industry 4.0 technologies improves decision making based on data throughout the project lifecycle (Lauria and Azzalin, 2024; Moshood et al., 2024). Deep learning-based DT systems may enhance automatic understanding and decision assistance during the design and building stages (Yang et al. 2024).

Experts might employ DT to observe progress on construction during actual time and make well-informed decisions depending on the condition of the structure (Arsecularatne et al., 2024; Wang et al., 2022). Wang et al. (2022) explain that by utilizing predictive features, DT offers future simulations that allow for the evaluation of different scenarios, calculation of their probabilities and cost assessments to identify the most optimal options for future work. The system helps site managers track progress, anticipate and address potential challenges, optimize resource use and ultimately boost project efficiency while minimizing risks (Moshood et al., 2024). Bakhshi et al. (2024) claim that although the difficulties in adopting DT into practice because of the large initial expense and significant technical know-how needed, several studies have found its benefits in terms of better decision making, management and teamwork. Furthermore they state DT makes it possible to simulate many situations, assisting stakeholders in forecasting results and making wise choices. The capacity is very helpful for handling logistics and foreseeing possible interruptions. Also, Wang et al. (2021) state the DT system continuously monitors the workspace and robot states using sensors, transmitting data to a VR interface for virtual scans. This allows experts to compare the as-built environment with the BIM, facilitating organizing tasks and decision making without physical hazards and stress.

2.1.5.6 Integration with emerging technologies

Effective use of DT during construction requires integration with smart technologies (Boje et al., 2020). The incorporation of digital technologies, including BIM, IoT, AI and DT into the construction industry improves efficiency, minimizes delays and develops sustainability (Piras et al., 2024; Hu et al., 2022). Immersive technology and DT can enhance construction safety, decision making, risk perception, productivity and together they encourage equal involvement by enabling remote collaboration and minimizing the requirement for on-site participation resulting in a more secure workplace (Wang et al., 2021; Yang et al., 2024; Wu et al., 2024). The DT system, which aims to enhance human-robot cooperation in the building industry, combines VR for activity planning, presentation and ongoing interaction, allowing human workers to efficiently oversee and direct robots (Wang et al., 2021). Moshood et al. (2024) express, by incorporating cutting-edge technologies like VR, AR, IoT sensors and radio frequency identification (RFID) tags, a smart construction site uses

DT technology to improve building steps. They state several research priorities arise, including the development of strong AI and ML algorithms for predictive capabilities and the exploration of blockchain for data privacy and traceability. Likewise Arsecularatne et al. (2024) state DT and blockchain integration is already popular across various sectors and it can successfully address concerns about possession of data, privacy, stakeholder availability and reliability. Also Yang et al. (2024) state DT offers notable enhancements in managing projects and execution when combined with BIM and AI. Additionally they investigate how ML can be used for autonomous evaluation of harm and predictive maintenance. The construction process offers considerable room for improvement, especially with the integration of automated systems that can perform various tasks, although single-function robots still depend on human supervision (Begić et al., 2022). Furthermore, building components can be autonomously examined by on-site discoveries, which can record flaws, modifications and updates based on IFC schema (Jiang et al., 2021).

2.1.5.7 Comprehensive participation

The application of DT can improve stakeholder participation during construction and the project management process (Arowoiya et al., 2023). DT may serve to help different stakeholders and make integration easier (Jiang et al., 2021). Yang et al. (2024) mention DT allows it to be simpler for project members to collaborate and communicate information effectively. As they point out, stakeholders in construction projects can model, track and evaluate the building's condition over time, improving comprehension of its operation, connections and performance. Zhang et al. (2024) highlight the value of multidisciplinary collaboration in order to improve building processes which combine expertise from several disciplines like mechanical engineering, civil engineering and AI. Bakhshi et al. (2024) discuss that in order to overcome obstacles and boost efficiency, coordination between stakeholders in a building chain of supply is essential. By offering one central location for interaction and knowledge sharing, DT helps stakeholders collaborate more effectively. This collaborative platform facilitates goal alignment and increases trust between supply chain participants. Nguyen and Adhikari (2023) summarize that the construction phase is characterized by continuous changes in facilities, equipment, materials, human and design, necessitating enhanced coordination and collaboration.

2.1.6 Advantages of digital twin technology in the construction industry

The advancements in DT technology influence a variety of areas, leading to diverse opinions. As Sepasgozar (2021) emphasizes, increasing productivity is DT's primary goal. However, there are numerous studies in the literature examining the threats as well as opportunities of DT technology in the building sector. Some primarily examine the cost aspect, few take a human centered approach, and others discuss it from the perspective of environmental impacts. Turner et al. (2021) indicate, the construction sector's productivity numbers will surely rise as a result of all the features it has. The benefits of DT in construction projects can be categorized as follows according to research in the literature: real time digital representation (Deria et al., 2022; Ellul et al., 2024), remote monitoring (Elfarri et al., 2022; Jiang et al., 2021), resource management (Hu et al., 2022; Orozco-Messana et al., 2022), safety management (Wu et al., 2022; Akanmu et al., 2021; Hosamo et al., 2022), risk management (Genc, 2021; Salem and Dragomir, 2023; Yang et al., 2024), collaboration with autonomous robots (Moshood et al., 2024; Hu et al., 2022; Li et al., 2021), waste reduction (Lydon et al., 2019; Lu et al., 2020a; Debrah et al., 2022), predictive decision making (Elfarri et al., 2022; Jiang et al., 2022; Turner et al., 2021), time and cost management (Genc, 2021; Bakhshi et al., 2024; Piras et al. 2024), communication and collaboration (Sabet and Chong, 2020; Zhang et al., 2024).

According to the literature, a key feature of a DT for real time digital representation is the dynamic visual simulation that integrates relevant data from the real environment (Deria et al., 2022). By combining history and present data from a building site, real time DT acts as only one source of knowledge (Ellul et al., 2024). The capacity to refresh modeled data in current time is essential for delivering current decision assistance (Yang et al., 2024). DT relies on actual time data to forecast future outcomes and enhance performance, which sets them apart from BIM (Nguyen and Adhikari, 2023). DT can provide a current picture of property status by monitoring metrics (Piras et al., 2024). Turner et al. (2021) give an example in their study that DT provides live captioned pictures with comments for people to see while watching particular spots on location, and it allows construction experts to observe overlays of details of construction in actual time on incomplete structures.

Elfarri et al. (2022) state, with DT, remote monitoring goes beyond observation to enable interaction with assets. This flexible framework supports diagnostics and analytics, such as tracking room occupancy and temperature variations in a house through sensor data. Additionally, digital twins can assist with equipment monitoring, guaranteeing precise and effective construction procedures (Jiang et al., 2021). Via remote monitoring, it improves failure prevention and identifies structural problems in the operation and maintenance stage (Hu et al., 2022; Chiachío et al., 2022). Similarly Khajavi et al. (2019) indicate also the DT might offer information on the structure's maintenance requirements.

In the context of resource management, Hu et al. (2022) state that DT offers advantages related to material use, such as optimizing structural design, reducing material consumption, and minimizing waste generation throughout the design and engineering stages. Furthermore, in the on-site construction phase it enhances the traceability of building materials. Similarly in the operation and maintenance period, durability monitoring is possible. Through quantitative evaluation, DT lead material flows in the direction of a sustainable material movement, for reuse and recycling after the end of life of the building (Hu et al., 2022; Orozco-Messana et al., 2022). Likewise, Sun et al. (2022) point out that assessing the material's condition is a time-consuming and labor intensive process therefore DT is very advantageous. By providing real time reliable data, a DT enables adaptive resource management by facilitating well informed decisions on workforce planning, material management and resource allocation (Piras et al., 2024). DT makes it possible to respond to output uncertainty by allocating resources efficiently like labor and materials (Bakhshi et al. 2024). Also in the construction stage, DT optimizes construction logistics (Hu et al., 2022; Yang et al., 2024).

Regarding safety management, DT helps reduce training-related risks and improve learning outcomes for construction professionals by offering a virtual practice platform during the construction phase of the building life cycle (Hu et al., 2022; Wu et al., 2022). Akanmu et al. (2021) state a DT framework aimed at reducing muscle injuries in construction labor by establishing an interactive mapping between employees' physical postures and their digital counterparts. In their study Hosamo et al. (2022) showed that through the detection of the operating errors, a few thousand dollars in yearly savings in energy were achieved. In the same way, Teizer et al.

(2022) suggest that it is important to consider DT for construction safety as a system based strategy that improves overall security performance, as opposed to only integrating sensory data.

In construction, risk management entails recognizing, categorizing, and evaluating hazards to understand their possible impact (Genc, 2021). In the AEC sectors, DT is viewed as a revolutionary instrument for risk management (Salem and Dragomir, 2023). Through the use of sensors, AR and VR devices, DT during building can improve security tracking and risk alert by taking pictures or videos of the actual site (Yang et al., 2024). DT allows early suspicious activity identification, which helps with predictive maintenance and building control (Akanmu et al., 2021). Hosamo et al. (2022) point out operational reliability is guaranteed and continuous tracking of performance is made possible via DT. It offers warnings for care and fixes, so faults can be found early and corrected before they get worse.

Autonomous robots are one of the most significant advances in Construction 4.0 which can carry out highly hazardous and routine tasks, minimizing the need for humans in hazardous situations (Moshood et al., 2024). Under the category of machinery works, within on-site construction, various advantages emerge (Hu et al., 2022). DT usage increases object detection reliability while minimizing constant mistakes and security threats (Li et al., 2021). Also it enables real time bidirectional performance, situational awareness capabilities for execution and workflow efficiency, autonomous robot production and remote interaction for communication and control between humans and robots (Hu et al., 2022; Li et al., 2021). The implementation of robotics may minimize labor lack, diminishing labor expenses and lowering exposure to hazardous circumstances (Akanmu et al., 2021). As the statistics reveal, 1061 deaths in the construction sector occurred in 2019, making up almost 20% among all job-related deaths in the US. In this context Wang et al. (2017) emphasize the importance of human-robot cooperation, especially in the context of assembly tasks. However, to combine the best human and robotic talents, training is necessary (Bilberg and Malik, 2019). Furthermore, Lucchi (2023) adds that using digitally generated predictions that combine human-computer and human-robot interactions should be guided by ethical considerations.

In terms of waste reduction, Lydon et al. (2019) emphasize that the scarcity of natural resources and their environmental impact are significant global concerns.

2050 Swiss energy targets, which require substantial upgrades in energy efficiency in both new and restored structures, are a result of these worries. Regarding sustainability, Lu et al. (2020a) state that with their ability to provide data on a building's water, energy, and waste generation, DT may help in the promotion of sustainable architecture. By allowing for improved monitoring and control of energy use, it helps minimize waste and support sustainable behaviors (Moshood et al., 2024). Also through real time emissions monitoring in the on-site construction phase, DT increases the potential for developing energy saving and emission decrease techniques (Debrah et al., 2022). In the light of the studies related to DT and energy efficiency in buildings, Liu et al. (2021) state monitoring energy is the most common use of DT. Overall, DT has a positive impact on sustainability concern including increased building energy efficiency (Hu et al., 2022; Khajavi et al., 2019).

DT, by enhancing prediction skills, can assist people who make decisions in avoiding unforeseen expenses and mistakes (Salem and Dragomir, 2023). DT can estimate forthcoming system states, create what if situations and make prescriptive suggestions with the help of AI and ML (Elfarri et al., 2022). DT in predictive maintenance employs ML to forecast circumstances, detecting flaws early and assisting in making decisions (Hosamo et al., 2022). Records from various sources can be put together and evaluated on a contemporary networked construction site to produce insights that better worksite management, increase safety and facilitate more effective decision making (Turner et al., 2021). The management advantages include site monitoring and indoor environment management both used in on-site construction and operation & maintenance stages (Jiang et al., 2022). Businesses that choose to utilize digital technologies want to give management quick access to quality information that will help them make better decisions, spot efficiency changes and cut expenses (Love and Matthews, 2019). Additionally it promotes smart city developments (Hu et al., 2023).

In construction, effective cost control and budgeting are essential to avoiding overspending and disputes. Effective time management is also essential to prevent delays brought on by scheduling mistakes (Genc, 2021). Detection of anomalies in smart structures assists managers in determining to meet project objectives with regard to both resources and time costs (Salem and Dragomir, 2023). DT with blockchain technology improves budget optimization by enhancing time management and teamwork in building supplies and increasing process openness and traceability (Bakhshi et al., 2024). Higher execution of time and enhanced scheduling are achievable by visual task tracking (Sabet and Chong, 2020). DT assists in identifying delays, inconsistencies and inefficiencies by comparing the actual site development with the projected timelines. This makes it possible for managers to modify plans, cut out pointless work and better distribute resources, simplifies processes for greater time and cost control during project execution (Piras et al. 2024).

Concerning communication and collaboration, Sabet and Chong (2020) state that the use of DT can foster a more collaborative environment and enhance interdisciplinary teamwork. Furthermore the satisfaction of stakeholders is increased by BIM and DT technologies' simplicity in transferring information, which helps them better comprehend another's job scope and minimizes possible misunderstandings or intervention. Similarly Moshood et al. (2024) mention DT enhances stakeholder communication, which eventually boosts the efficiency of the project. They also indicate that more organized communications are made possible by developing a DT from the beginning of a project according to results. Zhang et al. (2024) highlight the precise application and feedback of the concept can be ensured by effective collaboration between designers and contractors. Also the optimal construction solutions can be assured by effective collaboration between DT systems and constructed components. Therefore, interdisciplinary and multidisciplinary growth are made possible by intelligent construction.

2.1.7 Challenges of implementing digital twin in the construction industry

Adopting the notion of DT in building sectors presents problems, such as how to apply it most effectively in changing, real time contexts and how to properly offer data visualization to clients (Turner et al., 2021). In this context, when the concept is examined in more detail, there are many challenges using DT in architecture and construction sector such as adaptability (Opoku et al., 2024; Sun et al., 2022), data integration (Lu et al., 2020a; Ryzhakova et al., 2022), data management (Yang et al., 2024; Riaz et al., 2015), high-fidelity model (Bilberg and Malik, 2019; Lu et al., 2020a; Sun et al., 2022), interoperability (Boje et al., 2020; Lu et al., 2020b; Almatared et al., 2022), operation cost (Moshood et al., 2024; Ghosh et al., 2020;

Akanmu and Anumba, 2015), cybersecurity and privacy (Huang et al., 2020; Ghosh et al., 2020; Piras et al., 2024), skill and training (Bilberg and Malik, 2019; Arowoiya et al., 2023) and user interface (Boje et al., 2020; Sun et al., 2022).

In relation to the adaptability challenge, Sun et al. (2022) state that, to effectively reflect the current status of the physical world, a DT must evolve in harmony with real world conditions. This problem is one of the challenges when constructing the infrastructure for DT technology. Moreover they state the challenges of creating a live, two-way interaction between the actual and virtual twin is referred to as the real time connection problem. They claim the success of DT technology depends on this relationship since it provides realistic physical elements without sacrificing anything. Also as Opoku et al. (2024) indicate, for DT development to be successful, dependable network connectivity and the right IoT sensor devices must be selected and established to guarantee efficient live data transfer between the virtual copy and the actual object. Ensuring a seamless connection and precise data transfer forecast between the actual and online worlds is crucial (Piras et al., 2024).

Lu et al. (2020a) mention there are many major challenges to the creation of DT, especially in the topics of data integration. As they state, building a DT involves bringing together data from various diverse and independent sources, including real time sensors, building management systems, cloud services, and among others. Keeping up-to-date, quality information that is precise is a requirement for the DT to function as a trustworthy tool for making decisions. When combining data from numerous IoT devices with multiple types of data, such as raw information like picture and audio streams, this becomes an extremely important difficulty (Ryzhakova et al., 2022; Yang et al., 2024). Similarly Arsecularatne et al. (2024) claim problems with data integration still exist.

Effective data management is essential for developing DT as they rely entirely on the data they are built upon; furthermore, ensuring compatibility among diverse norms, procedures, and data formats across systems is a significant challenge (Yang et al.,2024; Lu et al., 2020a). As Riaz et al. (2015) point out, combining BIM data and sensor data flows is going to be difficult for conventional methods of data management because of the massive amount of data. Moreover, they discuss identifying limited values in the obtained data is one of the major challenges of actual time data from sensor flows, because sensor information may be lost for a variety of causes.

Sun et al. (2022) define the high-fidelity model challenge as a difficulty in producing a DT that exactly reproduces every characteristic of the original object. Also add that it describes a system's capacity to precisely imitate its actual environment in the DT. Additionally Lu et al. (2020a) state that DT is a virtual copy of real assets, incorporating AI, machine learning and data analytics to generate dynamic digital simulation models. These models can adapt and fix themselves using various data sources, aiming to precisely display and predict the conditions of their physical counterparts. Nonetheless, they highlight the challenge exists in developing these models and guaranteeing that they properly reflect their physical counterparts. An absence of high-fidelity modeling and the limited synchronization capabilities across physical and digital domains are two major obstacles (Bilberg and Malik, 2019).

Data interoperability stands out as a highly significant challenge within the AEC industry when it comes to DT (Almatared et al., 2022; Boje et al., 2020). Boje et al. (2020) point out that while there has been considerable advancement toward solving interoperability difficulties, such as converting model data into formats, there is still much work to be done before DT systems can be implemented successfully. Furthermore, Almatared et al. (2022) mention that despite a lot of effort to make data work well together in construction using different standards and computer tools, the industry still has trouble with losing data, data not fitting well and missing meanings when moving data between BIM applications. Data interoperability is problematic since it takes a lot of work to connect DT data from sensors to the model. Lu et al. (2020b) discuss creating new IFC entities to improve operation and management information management. Making sure the DT can use the provided data efficiently and enhancing data interoperability depend on the operational and maintenance stage (Nguyen and Adhikari, 2023).

Assessing the expenses linked to setting up and keeping a DT system is a challenge and the problem arises because there is often insufficient information available for evaluating these costs accurately, making it tough to manage DT systems effectively (Akanmu and Anumba, 2015; Moshood et al., 2024). Moshood et al. (2024) claim the need for advanced technology in its implementation makes it costly to operate. This is because it involves a lot of digital changes and a considerable initial expenditure. Likewise Jiao et al. (2024) point out there is still an initial expense associated with DT implementation in the construction industry and some countries may not use DT due to their expensive cost. Ghosh et al. (2020) indicate the financial evaluation of IoT based methods, including the anticipated long term financial gains, returns on investment and payback timeframes, has not yet been approved or confirmed. They add further research is necessary to determine the economic benefit of techniques at both the company and sector levels.

Cybersecurity is a significant global problem that affects all sectors and consumers, including the field of construction (Ghosh et al., 2020). Huang et al. (2020) indicate that because data is gathered and passed automatically without human oversight, there is a risk of cyber threats. This involves worries about how data is stored, accessed, shared and verified. The fact that data is collected and transmitted automatically can make the DT system a target for cyber-attacks, creating a serious problem during its operation. Additionally, they describe the privacy struggle that the worries people have about their information being collected automatically in DT systems. They further add that IoT device data generation might lead to possession conflicts, which is a privacy risk. Thus the vast amount of data from IoT technologies requires strong systems to manage it safely and privately (Ghosh et al., 2020). Piras et al. (2024) claim preserving privacy and securing sensitive information are essential components. To stop illegal access and violations, strong security measures along with data management standards are required. Moreover, since cyberattacks are growing more complex, deeper protections are needed. A proposal that may handle the cybersecurity and privacy struggle is also included in the literature. As a solution, studies propose blockchain technology to address data security, privacy and copyright issues, while also suggesting blockchain based data management model for DT to ensure data security (Huang et al., 2020; Sepasgozar, 2021; Teisserenc and Sepasgozar, 2021).

Bilberg and Malik (2019) point out, to effectively adopt and use DT technology, it is necessary to have appropriate knowledge of complicated information technology systems, which is where the skill and training challenge comes in. Training is required to integrate the finest human and robotic operational skills. This task highlights the significance of creating an easy to use DT interface that can be used by someone with no experience or a multidisciplinary team. Additionally, they mention system complexity relates to the difficulty of managing and interpreting the vast amount of information that is present in complex systems. Organizations need to train their workforce in fundamental digital technology skills, including DT, to effectively solve challenges in the construction industry (Arowoiya et al. 2023; Yang et al., 2024). The insufficient trained person increases the need for expensive consultants (Moshood et al., 2024).

Sun et al. (2022) express that a simple DT interface that can be applied by an unskilled human or a multidisciplinary group is required due to the user interface challenge. Users from various social and educational backgrounds need to be able to interact with the DT, which can change depending on the lifespan of the software categories. The researchers highlight that interface design itself is unable to assess how well human operators read digital twin insights and communicate with machines (Boje et al., 2020). When it comes to user input and the comprehension of DT outputs, it is crucial to create platforms that seamlessly integrate human interaction (Lu et al., 2020a).

Due to problems with integrating data, high-fidelity modeling, interoperability, real time interaction, operating expenses, cybersecurity and privacy worries, DT usage might be complicated (Piras et al., 2024; Almatared et al., 2022; Sepasgozar, 2021). Hu et al. (2022) add that the absence of standards, interoperability and data quality, in addition to the high cost of installation and maintenance, are some difficulties in integrating DT in building and construction firms. Similarly Arowoiya et al. (2023) identify multiple crucial elements affecting the adoption of DT, despite its advantages.

2.1.8 The potential of digital twin

The AEC sector is increasingly adopting digital technologies like BIM, IoT and AI for designing, constructing and managing buildings and infrastructure (Almatared et al., 2022; Bosch-Sijtsema et al., 2021). Many businesses, especially ones that are information intensive and need real time forecasting ability have enormous potential for DT, and there is a great opportunity for it to improve productivity, efficiency and making decisions in the construction sector (Liu et al., 2021). The progress of digital technologies like DT has helped many industries and it has the potential to solve problems in building construction projects (Nguyen and Adhikari, 2023). The construction industry currently uses DT, which is regarded as one of the most effective and significant methods to improve construction using construction 4.0 connections and enhance stakeholder cooperation (Jiao et al. 2024). Similarly Almatared et al. (2022) point out that due to the predicted advantages of DT technologies, such as increased productivity and efficiency, the AEC sector is using them more and more. As a result, there has been significant research focused on utilizing DT in this sector. The operation and maintenance phase is the subject of about 70% of the research that have been examined, and the most widely used DT uses are facility operation and maintenance, managing energy and structural health tracking (Liu et al., 2021). DT has continued to evolve rapidly as sensor technology that collects data from the real world has developed, such as low power requirements and wireless connectivity (Azfar et al. 2023). With DT adoption, IoT could also help employees operate as productively and effectively as possible (Ghosh et al., 2020). Elfarri et al. (2022) express the reason for exploring DT lies in their ability to provide potential financial savings and increased effectiveness. They state DT's capabilities span from description, diagnostics, prediction, adaptation to autonomy. The study highlights it can be utilized for remote house monitoring, gaining insights into the indoor environment, making predictions about future conditions, offering recommendations based on past behavior and autonomously controlling the house. Moreover, Akanmu et al. (2021) define the upcoming era of DT and cyber-physical systems as the incorporation of cyber and existing physical systems. Their overview includes possible applications of the forthcoming cyber physical system and DT for enhancing worker productivity, lifespan operations for construction processes as well as skills of employees, security and health. Also they state, DT may potentially facilitate the remote operation of robots for drywall installation, monitor and adjust worker posture, and prevent incidents between workers and construction equipment. Furthermore Sepasgozar (2021) indicates there is a growing need to create and apply DT since it may become a fundamental technology in numerous industrial areas. Figure 2.9 shows a DT capability level scale. In the initial three stages, the DT can furnish information or insights exclusively regarding past and current occurrences. Solid objects may set up standalone DT, which might be present even before the item is constructed. When an asset is installed and has sensors, data can be uploaded in current time to produce a descriptive data set that provides more information on the asset's condition.

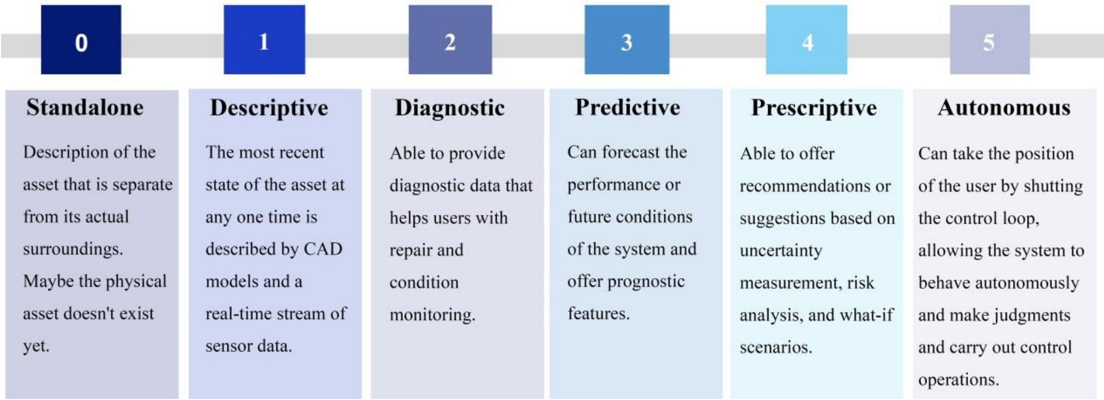

Figure 2.9 : A summary of a digital twin's capability stages, adapted from Elfarri et al. (2022).

Khajavi et al. (2019) state that, in terms of flexibility, even for buildings constructed using traditional pre-BIM practices, there is potential for improvement through the integration of a DT. This can be accomplished by using cloud based analytics tools and equipping the buildings with sensors. According to Zhang et al. (2022), DT technology can change how construction sites are controlled and observed by offering a framework that combines the digital and physical worlds. The goal of the suggested framework for applying DT to construction site management is to more effectively meet management requirements. Similar to them Lu et al. (2020b) offers an innovative approach for anomaly detection based on DT technology. This method has proven effective for providing ongoing asset monitoring for operation and maintenance, suggesting that DT can greatly enhance the identification and handling of anomalies in structures. This shows that DT may be more widely applied in the sector by being in line with the standards that are in place now. Unlike structure based approaches, Ham and Kim (2020) explore the potential of DT usage on a city level. With the help of real time data gathered from IoT sensors such as traffic, energy consumption, air pollution and water quality for controlling the complex structures of cities, the advantages of a DT city might be evaluated. Comprehending the physical sensitivity of cities might help policymakers analyze possible risks connected with metropolitan regions. A DT city with enhanced hazard visibility and urban connections is expected to aid risk-informed infrastructure decisions and support what-if scenarios during emergencies. Likewise Austin et al. (2020) highlight widespread implementation of sensor and communication tools that are firmly embedded in the real urban environment is going to be necessary to allow next generation smart city systems. They suggest creating a DT framework for smart cities that integrates machine learning with semantic knowledge representation and logic. Furthermore Hu et al. (2023) emphasize the potential for DT enhanced predictive maintenance (PdM). They claim that it would be beneficial to develop and include additional features, such as asset scheduling, cost savings and making choices into the software to help the construction sector achieve sustainability, predictability, security and effectiveness. Hosamo et al. (2022) indicate predictive maintenance is crucial since repair expenses account for approximately 65% of annual facility management costs. They insist predictive maintenance may lead to longer equipment life, greater efficiency, and lower labor costs. Rafsanjani and Nabizadeh (2023) indicate that the widespread adoption and application of these technological advancements are expected to result in significant cost reductions within the AEC industry. This is projected to amount to $950 million during the design and construction stages, as well as $400 million during the operation and maintenance phases in the non-residential AEC sector by the year 2025. Although proof supporting DT's effectiveness in lowering nonfatal harm, property controls, improving security, tracking progress and output, the DT adoption in the construction sector continues to be in its early stages (Akanmu et al., 2021).

In summary, the potential of DT includes general insights for the future, such as increased productivity and efficiency, the predictive advantages, potential financial savings, remote monitoring, the offering of recommendations, applicability of DT for existing buildings and autonomous control over individual structures and even complex urban structures. The DT provides solutions for the challenges that the construction sector primarily faces. As technologies such as AI, machine learning, sensor technology, cloud platforms and others continue to develop rapidly, the adoption of DT in the AEC sectors might become inevitable. Likewise, Yoon (2023) highlights the vast potential of DT in optimizing building operations, energy efficiency, air quality and carbon neutrality;however, systematic discussions on digital twin modeling in the building sector remain limited.

2.2 Productivity

The term productivity was first used in an essay by Quesnay in 1766. Over a century later, in 1883, Littre characterized productivity as the faculty to produce, expressing the tendency or motivation to generate output. Also defined officially in 1950 by the Organization for European Economic Cooperation as a ratio derived by dividing output by one of the production factors. It is possible to think of construction productivity as an evaluation of the outputs that result from an arrangement of inputs (Jarkas and Bitar, 2012). Likewise Rathnayake and Middleton (2023) explain the meaning of productivity as a crucial measure of performance that is determined by dividing output by input. Whereas Ghoddousi and Hosseini (2012) define as the produced units divided by the related labor hours. Vogl and Abdel-Wahab (2014) examine effectiveness and believe that productivity is a metric of how effectively the economy converts its inputs to output. Similar to them Hiyassat et al. (2016) state how quickly tasks are completed is measured by productivity. Productivity has numerous definitions given by various studies; in overall, it can be described as the ratio of output to input (Alzubi et al., 2023). However, Hasan et al. (2018) mention the diversity of production specifically in the construction industry, stating that the units of measurement vary with construction activities based on input and output types. Nevertheless, the significance of productivity in cost reduction and profit generation is universal across all industries, including the construction sector. They summarize that in every sector, productivity is a critical factor to take into account and there are various ways of describing it based on the situation. Naoum (2016) summarizes the explanation of productivity as the greatest possible amount of output while minimizing input. The Cambridge dictionary (2024) defines productivity as the speed at which a business or nation produces products, typically measured in relation to the quantity of labor and resources required to generate them. Also, it gives the meaning that the capacity to complete as much work as possible in a given amount of time. Oxford dictionary (2024) explains the speed that an employee, business, or nation creates items and the quantity produced in relation to the resources (money, labor, and duration) required to generate things. Ghate et al. (2016) indicate productivity is an essential element of the construction sector and might be used as a measure for efficiency of output.

2.2.1 Productivity and construction industry

Among the industries with the lowest productivity is the construction industry (Rathnayake and Middleton, 2023; Turner et al., 2021). Globally, the construction sector has been defined by a notable decline in productivity (Laszig et al., 2020; Teisserenc and Sepasgozar, 2021). The industry faces a shortage of worker abilities, an inadequate innovation and an unpredictable future as well as low productivity (Yang et al., 2024). Moreover Alzubi et al. (2023) indicate construction projects experience productivity declines ranging from 40% to 60%. Also the building sector has an unimpressive history of advancing efficiency and productivity (Lydon et al., 2019). Although improvements frequently result in higher efficiency, the construction sector has fallen behind other industries in integrating new technologies into its operations (Menegon and Filho, 2022; Laszig et al., 2020; Moshood et al., 2024). As Laszig et al. (2020) claim, nonetheless, advancements are a major factor in the rise in productivity across a wide range of sectors according to past studies and experiences. On the other hand Akanmu et al. (2021) point out even with greater attempts to enhance the execution of construction projects methods, the sector continues to face challenges related to decreased productivity, security and quality. Turner et al. (2021) state, enhancing productivity is crucial as it serves as a key indicator of living standards within countries and their potential for economic growth. Additionally they state low productivity and skill gaps have resulted in increased construction costs, project delays and inadequate sustainability procedures in the construction industry. Furthermore they point out, under the construction 2025 plan, the government of the United Kingdom has set goals for building projects that include a %50 quicker completion time, %50 fewer emissions of greenhouse gases in the constructed environment, and a %33 decrease in both the starting price of construction and the property's entire lifespan expense. Likewise Teisserenc and Sepasgozar (2021) mention the conflict pricing strategy and the weak financial system of the sector in their paper. Hiyassat et al. (2016) add, increasing profit in the construction industry with minimal or no expense changes can be achieved via boosting productivity. Additionally Vogl and Abdel-Wahab (2014) mention that in all nations, productivity is a major factor in economic expansion and success. Moreover, enhancing productivity in the construction industry could lead to significant cost reductions in addition to increased profits and revenues for the industry. Alzubi et al. (2023) indicate keeping track of construction productivity is crucial for the success of construction projects as it enables the evaluation of project performance. Additionally they claim poor construction productivity continues to be considered one of the most significant problems in the construction sector, despite the many obstacles it faces. They also emphasize automated monitoring techniques may successfully identify and improve construction productivity variables, with vision based technologies (37%) finding to be most efficient. Rafsanjani and Nabizadeh (2023) claim the global AEC industry has an estimated cumulative value of US$11.72 trillion in 2021 and is projected to reach US$12.26 trillion by 2023. Therefore, the sector has consistently looked for ways and methods to optimize resource utilization, improve productivity, lower project costs, increase worksite security and reduce project completion time. Furthermore they add that the AEC industry will see significant savings in expenses as a result of the widespread demand for and use of technology improvements, with the non-residential AEC sector projected to save US$400 million in operation and maintenance stages by 2025 and US$950 million in design and build phases. Due to an increasing understanding of the substantial role played by the construction industry in promoting an economy that succeeds, the importance of productivity growth is gaining more significance for stakeholders in the industry (Adebowale and Agumba, 2023). Alzubi et al. (2023) indicate the construction sector lacks excellent timing and budget management in the execution of megaprojects. Approximately 77% of such projects are projected to face delays exceeding 40%, while cost overruns exceeding 30% are observed in 98% of cases. Ineffective productivity stands out as a primary contributor to these unsatisfactory project outcomes. Likewise Akanmu et al. (2021) express that the AEC sector is constantly looking for new and creative ways to complete projects on schedule, within budget and with security. They argue that industry 4.0 claims to increase production, decrease waste and raise project efficiency; however, the acceptance of numerous advances in technology will be crucial for the increased productivity. Si et al. (2023) indicate using these industry 4.0 innovations lowers operating expenses while boosting speed and accuracy.

Productivity within the construction sector is commonly measured on the levels of activity, project, and industry (Adebowale and Agumba, 2023). According to studies there are 3 common productivity measurements utilized in the construction industry

(Rathnayake and Middleton, 2023; Zhan and Pan, 2020; Zhi et al., 2003; Arditi and Mochtar, 2000). Initially, there is an economic model that characterizes productivity as total factor productivity, representing the ratio of total outputs, in dollars, to total inputs, also expressed in dollars. These inputs encompass labor, materials, equipment, energy, and capital. Policymaker agencies adopt to assess the economic condition of the country. The second model, specific to individual projects, characterizes productivity as total productivity. This is the ratio of outputs measured in physical units (such as square feet) to inputs expressed in dollars. The inputs in this model encompass labor, equipment, materials, and management. This model is more precise and applicable to both governmental agencies and the private sector. The third model is activity-oriented, defining productivity as labor productivity. This refers to the ratio between outputs measured in specific physical units (such as tons of steel) and inputs expressed in labor hours, where the inputs consist just of labor. The model proves beneficial for producers in computing project costs and monitoring on-site activities. However, Rathnayake and Middleton (2023) underline the requirement for multi input descriptions of productivity in order to offer an evaluation that is deeper. The total cost of labor or employee hours is commonly employed as a metric in construction, and the outcome is typically expressed in terms of weight, length, or area (Hiyassat et al., 2016).

Numerous academics have shown that increasing construction productivity is a continual, scientific process as opposed to an only once event that happens during a project's life cycle (Ranasinghe et al., 2012). Intelligent approaches to increase construction productivity are desperately needed, especially in terms of employee and management concerns (Hasan et al., 2018). According to Opoku et al. (2021), the construction sector faces many difficulties, such as low productivity, but DT technology has the power to change this business and offer solutions for these difficulties. In the similar way, Turner et al. (2021) state that the demand for greater efficiency together with the complex nature of site construction projects has raised curiosity about the possible applications of Industry 4.0 technology such as DT, AI, sensors, automation, BIM and wearables. Moshood et al. (2024) add, facing critical challenges requiring innovations, such as improving sustainability, efficiency and productivity. Laszig et al. (2020) state the efficiency of the AEC sector can be revolutionized in a number of innovative areas by major improvements already in use or in development of new building materials, digital technologies and robotics. Also it is clear that innovation and new technology significantly boost productivity and the key areas include digitalization, construction automation, resource efficient and recyclable building products, and new service models. Ling et al. (2023) indicated that five technologies especially give relative benefit to the firms in relation to the closest competitors of AEC companies. The adoption of cloud-based technology, design for manufacturing and assembly, IoT, robotic technology and AI had a strong correlation with higher project quality, productivity, and a good brand name. Similarly Zhan and Pan (2020) point out, the main goal of supporting innovative technology is to speed up the process of industrialization and mechanization by supporting labor-saving and successful construction management innovations, which will boost productivity and make it possible to replace labor with capital or materials. As Love and Matthews (2019) highlight, innovations boost productivity and performance in 3 main ways: processes that are already in place are streamlined by automation, new practices are supported alongside established ones by extension, and traditional methods are replaced with digital alternatives by transformation.

2.2.2 Factors affecting productivity in the construction phase

Politicians and the building sector put a high priority on increasing productivity because it directly affects efficiency (Mehta et al., 2022). Productivity is increased in construction projects when technology is used (Hiyassat et al., 2016). Nevertheless, unfortunately the construction sector's rise in productivity is noticeably behind compared to all other industries (Abdel-Wahab and Vogl, 2011). Construction productivity might be impacted by a wide range of variables, including the climate, work environment and situations, manpower expertise, training and motivation, as construction projects are labor intensive that are open to interior and exterior conditions (Hasan et al., 2018). Ghoddousi and Hosseini (2012) explore the concept of boosting productivity by the use of factors that have beneficial consequences and effectively dealing with or controlling those that have negative impacts. While the primary constraints on productivity may vary across projects, businesses, and locations, the authors identify common patterns in issues which limit efficiency. Their research highlights that the management system and strategies, encompassing skills in management, scheduling, material and equipment management, along with quality control, stand out as the most influential factors affecting construction productivity. Additionally, following closely behind in influence are factors such as labor force, the industry environment, and external influences. Likewise Arditi and Mochtar (2000) state the findings show that the functions with the most potential for productivity growth are cost control, time management, design methods, employee training, and quality management. In contrast Alzubi et al. (2023) and Ghoddousi and Hosseini (2012) claim the most significant elements influencing construction productivity are those related to labor. Alzubi et al. (2023) explains the rest of the ranking as follows; labor factors followed by management and jobsite factors which hold equal importance, and lastly, external factors. On the other hand El-Gohary and Aziz (2014) assert the management category rated at the top, the labor category came in second and followed by the industrial category in third. Alzubi et al. (2023) identified 18 factors that predominantly influence construction productivity. These factors can be categorized into 4 groups. The first category encompasses management-related factors, including supervision, resources, security, cost, and schedule. The second category involves workforce related factors, such as abilities, background, fatigue, unplanned pauses, lateness. The third classification relates to jobsite factors, including revisions, rest areas, busy locations, site layout and complexity of design. The final category encompasses external factors like weather, regulations, and owner influence. The groups Rathnayake and Middleton (2023) list that affect productivity are: labor, technology and equipment, construction site, schedule, supervisors and materials. According to Jarkas (2015) the following factors impact productivity: worker abilities, coordination between design professions, lack of labor monitoring, mistakes and inaccuracies in design drawings, revision, working additional hours, absence of a reward system and adverse weather conditions. Similarly, Heravi and Eslamdoost (2015) mention labor competence, decision making, motivation, site layout, and planning as the main five elements impacting employee productivity. Even with this optimistic prediction, they claim productivity could rise by 37% to 48% if each of these characteristics were improved. Naoum (2016) has taken a managerial approach to the problem and explains problems related to productivity from the management perspective. Then lists factors such as insufficient project scheduling, delays created by mistakes in design and change commands, workplaces, performance limitations on employees, aesthetic and buildability-related problems, leadership and organizational methods, procurement techniques, absence of the adoption of the project's management information system. Teisserenc and Sepasgozar (2021) claim that the absence of financial transparency in the AEC sector results in poor productivity, reduced cost savings and restricted cooperation and information sharing. Therefore they suggest smart contracts to automate procedures in order to save money, increase efficiency and minimize time. Hasan et al. (2018) emphasize certain variables reoccur in multiple research. Therefore, they argue that the frequent citation of these issues in research over the past three decades highlights their importance and continued presence as barriers to construction project productivity. Also researchers show the top ten frequently mentioned limiting building output worldwide the following, in decreasing sequence of significance: Lack of access to materials, insufficient oversight, limited expertise, poor tools and equipment, unfinished designs and specifications, weak conversations, reworking, improper site layout, unfavorable climate circumstances and changes. As Mehta et al. (2022) indicate, while numerous studies have explored ways to improve specific efficiency factors in construction projects, few provide a comprehensive view of how inefficiencies impact projects as a whole. They further explain the sector will benefit from identifying the root causes of significant project errors and implementing prevention strategies.

We can identify 7 key factors that challenge the AEC sector and impact productivity during the construction phase based on the research papers reviewed as illustrated in Table 2.5. These factors include labor, management systems, work site, industry environment, design related issues, climate and communication. Challenges in these areas lead to a significant decline in productivity. They can be categorized to identify the key areas of concern.

Table 2.5 : The factors affect productivity in the construction phase.

Category of Factors	Subcategories	References
Labor	Skill Training Motivation	Alzubi et al. (2023), Hasan et al. (2018), Jarkas (2015), Durdyev et al. (2018), Mehta et al. (2022), Ghoddousi and Hosseini (2012), Heravi and Eslamdoost (2015), Rathnayake and Middleton (2023), Rivas et al. (2011), Adebowale and Agumba (2021), Arditi and Mochtar (2000)
Management System	Cost Management Quality Management Time Management Material and Equipment Management Desicion Making Ability Organizational Methods	Rathnayake and Middleton (2023), Ghoddousi and Hosseini (2012), Durdyev et al. (2018), Naoum (2016), El-Gohary and Aziz (2014), Alzubi et al. (2023), Heravi and Eslamdoost (2015), Hasan et al. (2018), Mehta et al. (2022), Arditi and Mochtar (2000)
Work Site	Site Layout Site Location	Heravi and Eslamdoost (2015), Jarkas (2015), Ghoddousi and Hosseini (2012), Alzubi et al. (2023), Naoum (2016), Rivas et al. (2011), Rathnayake and Middleton (2023), Hasan et al. (2018)

Table 2.5 (continued) : The factors affect productivity in the construction phase.

Category of Factors	Subcategories	References
Industry Environment	Financial Uncertainties Regulatory Changes	Mehta et al. (2022), Durdyev et al. (2018), Genc, (2021), Jarkas (2015), Teisserenc and Sepasgozar (2021), Hasan et al. (2018), Ghoddousi and Hosseini (2012)
Design Related Issues	Constructability Inaccuracies in Drawings	Rivas et al. (2011), Rathnayake and Middleton (2023), Naoum (2016), Jarkas (2015), El-Gohary and Aziz (2014), Jarkas and Radosavljevic (2013), Mehta et al. (2022), Hasan et al. (2018)
Climate	Adverse Weather Conditions	Jarkas (2015), Alzubi et al. (2023), Hasan et al. (2018), El-Gohary and Aziz (2014), Heravi and Eslamdoost (2015)
Communication	Misunderstanding Commmunication Barriers	Jarkas and Radosavljevic (2013), Heravi and Eslamdoost (2015), Jarkas (2015), Mehta et al. (2022), Mahamid (2013), Rivas et al. (2011), Hiyassat et al. (2016)

2.2.2.1 Labor

Labor aspects play a key role in the productivity of construction and the results show that the labor market is currently not benefited enough to increase construction productivity (Zhan and Pan, 2020; Lee et al., 2023). Since construction is a labor intensive business, worker payments commonly account for between 30% and 50% of the project's total cost (Heravi and Eslamdoost, 2015; Durdyev et al., 2018). However Lee et al. (2023) state that the number is even higher and claim labor costs account for approximately 40–60% of overall construction expenses. They also point out through increasing labor productivity by 10%, companies in the UK may save GBP 1.5 billion. Mehta et al. (2022) express that According to the Associated General Contractors of America, worker problems that affect productivity account for over 60% of construction project delays or cancellations. Within the labor category, the most significant element influencing construction productivity is the skills and expertise of the employees (Alzubi et al., 2023; Jarkas, 2015; El-Gohary and Aziz, 2014). Durdyev et al. (2018) claim that besides the workforce's abilities and expertise, motivation is also vital. Likewise Mehta et al. (2022) identify motivation as one of the key factors with labor skill and experience affecting productivity. El-Gohary and Aziz (2014) state incapable workers with inadequate training frequently exhibit low and inaccurate outputs. Also in the opinion of Jarkas (2015), highly qualified staff members can solve problems logically and with advanced technical capabilities, which leads to greater quality of final output. Expert workers are able to do jobs faster and with greater quality (Heravi and Eslamdoost, 2015). Adebowale and Agumba (2021) also highlight issues such as workers' abilities, insufficient training, and the need for rework in various construction industries. Rivas et al. (2011) note that having under qualified workers in important roles could demoralize workers in employment. While problems like not enough education, low motivation and insufficient management lower productivity, an experienced, motivated team increases it (Durdyev et al., 2018). Additionally, regarding the other factor climate, Pamidimukkala et al. (2023) states that due to workers performing tough physical duties in adverse weather conditions, they are exposed to long-term health issues which cause low efficiency in the long term.

2.2.2.2 Work site

Traffic, site layout, restricted work area and limited entry are some examples of variables that might reduce productivity by generating logistical problems and inefficiencies on construction sites (Jarkas, 2015; Ghoddousi and Hosseini, 2012). Heravi and Eslamdoost (2015) draw attention that a carefully planned site layout may boost worker productivity from 12.2% to 19.8%. They define site layout as the strategic placement of temporary buildings, utilities, main equipment, stores, offices and access routes. Similarly Alzubi et al. (2023) and Naoum (2016) discuss a well planned site layout is essential. Also they indicate the site being crowded is highly influential in this matter. Rivas et al. (2011) highlight the critical impact that the work site has in assessing productivity. Based on the study, there is a considerable impact on productivity from factors such as the access of materials and the arrangement of the workplace. Likewise, Rathnayake and Middleton (2023) highlight these factors that affect how effortlessly processes are executed on-site, greatly impacting construction efficiency.

2.2.2.3 Management system

Durdyev et al. (2018) and El-Gohary and Aziz (2014) find the management category the most significant in influencing productivity so rated at the top. Efficient material and equipment management, appropriate planning, well supervision and decision making procedures are essential variables that improve productivity (Rathnayake and Middleton, 2023; Naoum, 2016; Durdyev et al., 2018). Reliable procurement techniques ensure resource availability when required, minimizing delays and thus improving the performance of the project as a whole (Rathnayake and Middleton, 2023; Heravi and Eslamdoost, 2015; Ghoddousi and Hosseini, 2012). Sustaining productivity requires careful scheduling and inadequate oversight has adverse consequences on it (Alzubi et al., 2023; Hasan et al., 2018). Mehta et al. (2022) discovered a significant misunderstanding about unreasonable scheduling among project participants. Also they point out the building sector has been troubled by problems like inadequate management and low quality. Heravi and Eslamdoost (2015) describe poor decision making as the result of incorrect reasoning, emotions, insufficient knowledge, unsuitable selections or problems in modifying the sequence and allowing approval. They claim strengthening it may raise labor productivity from

15.6% up to 19.8%. Moreover they discuss leadership, interaction and management techniques concentrating on organizational and individual variables to enhance results. Similarly Naoum (2016) points out the leadership approach taken on the job site can have a big influence on output. They further discuss that effective management and leadership styles are crucial for controlling work activities from design to construction, which is essential for achieving high productivity. Effective leadership approaches can significantly reduce time and costs, with good management style greatly influencing productivity (Durdyev et al., 2018; Naoum, 2016).

2.2.2.4 Industry environment

Mehta et al. (2022) explain that industry environment factors, often known as political or extreme circumstances, are uncontrollable occurrences including pandemics and political instability. Due to interruptions, increased expenses or the need for plan modifications, these variables may have an enormous effect on building projects. They claim these are huge inefficiencies that cause timetable and financial conflicts because of their unpredictability. Mashood et al. (2024) claim regulatory issues provide serious obstacles to the sector. Those obstacles that can slow down or make execution more difficult in the construction ındustry. Challenges could include handling complicated regulatory systems, getting required approvals, and following current standards. Likewise Durdyev et al. (2018) state sustaining productivity requires both strong financial management and predictability. They also discuss financial circumstances and regulatory permissions that may result in unforeseen cancellation, needing backup plans to minimize their effects on operations. Genc, (2021) expresses uncertainties as financial issues like pricing speculation, the rate of inflation and unforeseen modifications to laws and regulations. Jarkas (2015) highlights how labor productivity is impacted by constant modifications in law and delays in statutory permits.

2.2.2.5 Design related issues

Rivas et al. (2011) mention that issues with design understanding and the requirement for more technical data can result in lost productivity. Insufficient designs and specifications, engineers not knowing the field circumstances and doubt frequently represent the causes of these problems. Constructability is one of the key factors influencing productivity (Rathnayake and Middleton, 2023; Naoum, 2016). El-Gohary and Aziz (2014) defined it as the ability to achieve project objectives by effectively utilizing construction experience in design, planning, procurement and operations. They point out enhancing the degree of constructability in designs is undoubtedly a beneficial initial move. Similarly Jarkas (2015) explains that buildability leads to rework thus impact productivity. Furthermore, errors in drawings that could cause delays and revisions raise project expenses (Rathnayake and Middleton, 2023; Hasan et al., 2018; Jarkas, 2015).

2.2.2.6 Climate

As stated by Jarkas (2015), poor weather has the tenth highest impact on labor productivity in the construction industry. He remarks that the result is in line with research from Qatar, India, New Zealand, US and Iran. Alzubi et al. (2023) claim since building operations usually take place outside, weather conditions including heat, humidity, storm and rain have an enormous effect on productivity. In their study, weather is regarded as the most significant external factor that can be observed using automated monitoring technologies, with a weight of 50.9%. Heravi and Eslamdoost (2015) express unsuitable weather, including extremes in humidity, temperature and snowstorms, has been shown to have a negative impact on production. In addition, they state location circumstances and weather are two of the main factors influencing operating efficiency.

2.2.2.7 Communication

Although there are many variables that influence construction workers' productivity, motivation is one of the most crucial ones (Jarkas and Radosavljevic, 2013). Employees that are motivated are typically more effective and dedicated to their work, which produces higher levels of production and boosting labor motivation could lead to a 12.7% to 14.2% increase in productivity (Heravi and Eslamdoost, 2015). Ineffective communication and collaboration may result in rework which lowers productivity and brings about disappointing results (Jarkas, 2015). Mehta et al. (2022) state communication issues can lead to misunderstandings and arguments. Further they emphasize effective communication and eventually a construction project's success depends on recognizing the differences in opinion shared by stakeholders such as engineers, contractors and architects. Mahamid (2013) notes that the lack of cooperation and communication among stakeholders is one of the top five elements that have an adverse effect on labor productivity in construction projects. Also Rivas et al. (2011) point out poor coordination can impact both motivation and productivity.

2.2.3 Productivity and digital twin

To comprehend the trends in productivity and DT research within the literature, a bibliometric study was conducted. We collected research from the Scopus database about DT, productivity and the building industry. Various document types, encompassing conference papers, articles, reviews, book chapters, books, and conference reviews, were taken into account. No time restrictions were applied, except for the language; only papers written in English were included. The Scopus advanced search engine was employed, utilizing filters based on Title-Abstract-Keywords. The code used for the search was TITLE-ABS-KEY ("digital twin") AND TITLE-ABS-KEY ("construction project" OR "construction industry" OR "construction sector") AND TITLE-ABS-KEY ("productivity" OR “efficiency”) AND (LIMIT-TO (LANGUAGE, "English")). A total of 134 publications were identified during the search. 10 significant contributors in this field are recognized and presented in Table 2.6 based on Scopus. The studies generally examine the effects of DT on productivity and the potential to boost efficiency in the construction sector. Additionally, these studies also discuss the supporting technologies for DT in enhancing productivity in the construction sector, as well as their use cases. Boje et al. (2020) explain that despite advancements of BIM, its lack of integration remains problematic. They suggest that combining AI, IoT and sensor technologies could evolve BIM into a more advanced DT, enabling real time, intelligent and sustainable construction practices. Opoku et al. (2021) examine DT technologies across the construction lifecycle, identifying six key applications including BIM, monitoring, logistics and energy simulation. They state the importance of adopting DT to maintain industry competitiveness. Sepasgozar (2021) focuses on defining DT roles and expanding digital shadow practices, noting the rising use of DL, robotics and blockchain. He emphasizes the key distinction of DT’s data flow. Turner et al. (2021) identify major research gaps toward a fully digital construction site. They argue for a systems based approach integrating Industry 4.0 technologies and point out the need for a deeper exploration over the next decade.

Table 2.6 : The most cited publications on DT and productivity in the construction industry.

No	Author	Title	Citation	Journal	Research Focus
1	Boje et al. (2020)	Towards a semantic construction digital twin: Directions for future research	622	Automation in Construction	Emphasizes the need for a Construction DT (CDT), identifies its capabilities, highlights key research challenges, and addresses the limitations of BIM.
2	Opoku et al. (2021)	Digital twin application in the construction indusrty: A literature review	322	Journal of Building Engineering	Examines the development of the DT concept, key technologies, six application areas across project lifecycle stages, and its implementation in the construction industry.
3	Sepasgozar (2021)	Differentiating digital twin from digital shadow: Elucidating a paradigm shift to expedite a smart, sustainable built environment	181	Buildings	Distinguishes DT from other digital modeling approaches, emphasizing its integration with blockchain and deep learning to advance efficiency within Industry 4.0 frameworks.
4	Turner et al. (2021)	Utilizing industry 4.0 on the construction site: challenges and opportunities	140	IEEE Transactions on Industrial Informatics	Mentions the potential of DT, smart wearables, and intelligent assets to improve construction processes, emphasizing the integration of data analytics, robotics and industrial connectivity to enhance productivity and safety.

Table 2.6 (continued) : The most cited publications on DT and productivity in the construction industry.

No	Author	Title	Citation	Journal	Research Focus
5	Love and Matthews (2019)	The "how" of benefits management for digital technology: from engineering to asset management	116	Automation in Construction	Investigates the importance of organizations engaging with digital technologies to enhance their competitiveness and deliver assets more effectively and efficiently.
6	Hosamo et al. (2022)	A digital twin predictive maintenance framework of air handling units based on automatic fault detection and diagnostics	107	Energy and Buildings	Highlight fault detection, diagnosis and predictive maintenance across systems, adopting AI and machine learning to improve maintenance and operational efficiency.
7	Debrah et al. (2022)	Artificial intelligence in green building	96	Automation in Construction	Highlights the integration of AI, DT, blockchain and robotics to enhance sustainability and efficiency, while addressing associated legal, ethical and moral challenges.
8	Lydon et al. (2019)	Coupled simulation of thermally active building systems to support a digital twin	86	Energy and Buildings	Emphasizes energy efficiency and productivity in construction, using simulation methods and a digital twin approach during the design and operation phases of building projects.

Table 2.6 (continued) : The most cited publications on DT and productivity in the construction industry.

No	Author	Title	Citation	Journal	Research Focus
9	Akanmu et al. (2021)	Towards next generation cyber-physical systems and digital twins for construction	83	Journal of Information Technology in Construction	Explores the integration of Cyber-Physical Systems and DT to improve efficiency, safety and performance through automation, real-time monitoring, risk management and advanced technologies like deep learning and augmented reality.
10	Teisserenc and Sepasgozar (2021)	Adoption of Blockchain Technology through Digital Twins in the Construction Industry 4.0: A PESTELS Approach	79	Buildings	Examines the integration of blockchain with DT in the BECOM sector under Industry 4.0, introducing the Decentralized Digital Twin Cycle (DDTC) to enhance collaboration, transparency, and data integrity through BIM and IoT.

Love and Matthews (2019) state that digital technologies can enhance asset value over its lifecycle. They underline the need for a structured benefits management approach as construction adopts BIM, IoT and DT. Hosamo et al. (2022) explore how DT can enhance facility management and maintenance through predictive and adaptable strategies. Their model integrates IoT, BIM and ML for defect detection and lifecycle optimization. Debrah et al. (2022) review AI in green buildings, highlighting how data mining and AI enable real time optimization. They suggest integrating AI with blockchain and DT to enhance sustainability. Lydon et al. (2019) propose DT based simulation for thermal systems embedded in lightweight roofs. They connect sensor and virtual data to reduce planning time and support multifunctional design. Akanmu et al. (2021) discuss integrating DT and cyber physical systems to improve construction efficiency, safety and risk management. Real time tracking and automation are emphasized as key benefits. Teisserenc and Sepasgozar (2021) propose the decentralized DT cycle framework to integrate blockchain with DT. They mention the role of smart contracts in overcoming trust and collaboration barriers.

When we look at the most cited studies, we can commonly say that they discuss the use of innovative technologies together with DT and its benefits for the construction sector. DT have also been approached from different perspectives, addressing their impact on the building life cycle, sustainability, construction economy and the future of the building industry. The key aspects research papers primarily focus on may consist of how DT differs from previous technologies, the innovations it introduces and the potential applications of DT alongside current emerging technologies. The limitations of the studies generally stem from the inability to apply the technology to a physical structure, the lack of practical experiments, conducted experiments that remain at the project level and cannot be more comprehensive and the limited data.

3. METHODOLOGY

3.1 Research Design

Despite the significant body of research on digital twin (DT) in the construction sector, there is a limited number of studies specifically exploring its impact on productivity during the construction phase. The aim of this study is to first identify the factors affecting productivity in the construction phase through a literature review and then determine the benefits, challenges and major applications of DT in the construction phase using the same approach. Based on these findings, the study examines how DT technology can help reduce challenges associated with construction productivity factors and evaluates its potential to enhance and improve construction efficiency.

The objectives of this thesis are as follows:

1) To explore the role of DT throughout the building life cycle in the construction sector
2) To identify its benefits, challenges, and key application areas in the construction stage
3) To determine the factors affecting productivity during the construction phase
4) To compare these factors with the DT system's identified capabilities to assess its potential in overcoming productivity challenges

To successfully achieve the research objectives, this study adopts two stage methodology: first a literature review on DT and productivity, second a questionnaire survey. Figure 3.1 provides a diagram of the methodology.

The literature review of this study consists of two sections: one focusing on DT and the other on productivity.

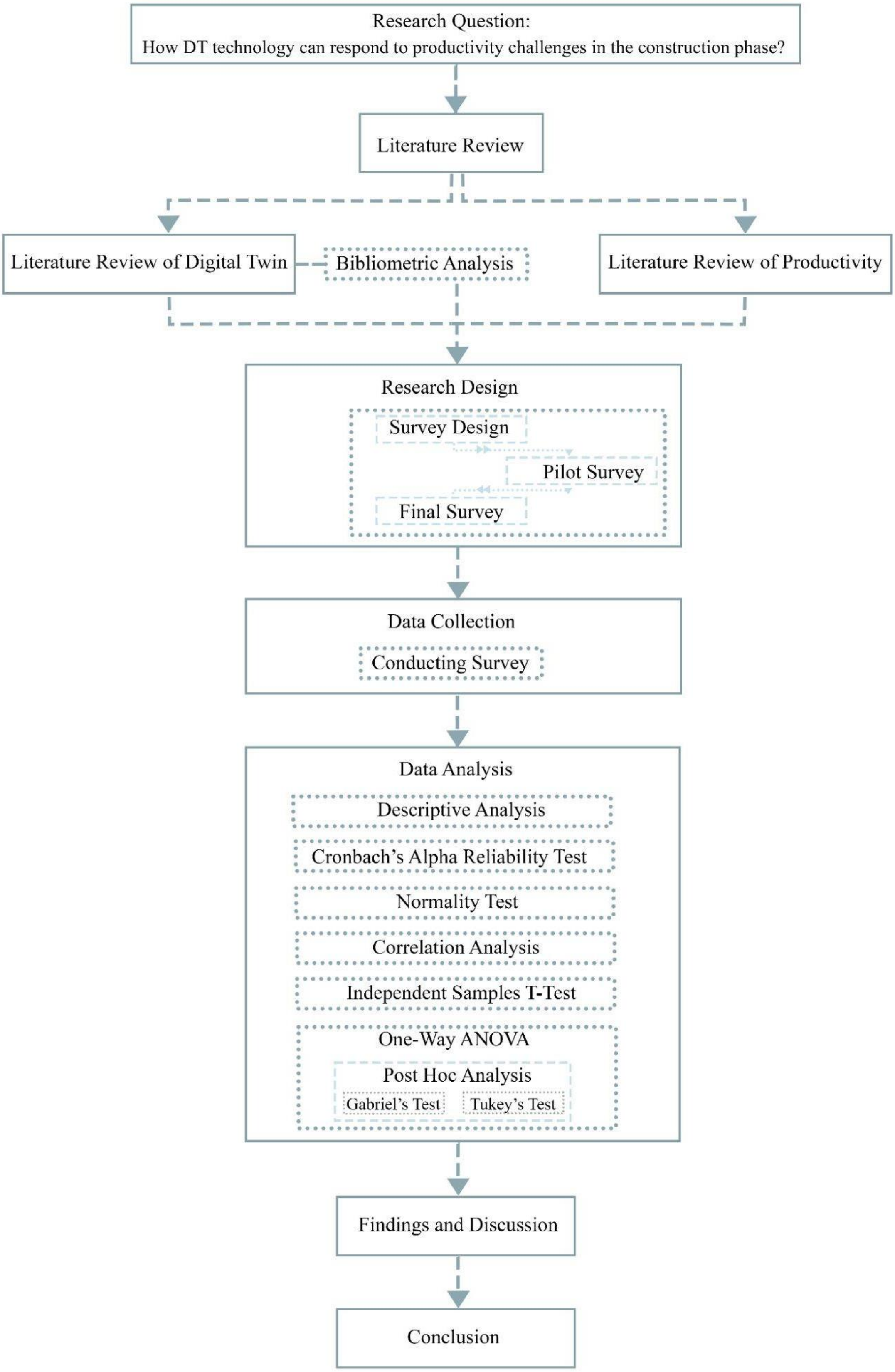

Figure 3.1 : The flowchart of the methodology.

For an in-depth analysis, research on the construction sector, its relationship with DT and productivity was collected from the Scopus database, including conference papers, articles, reviews, book chapters, and books. While no time restrictions were applied, the study focuses on English language research. The DT section of the literature review examines several key aspects, including its definition, the technologies it integrates with, its general applications, its architectural and construction related applications, and its role within the building life cycle. Additionally, the study determines the benefits of DT, the challenges associated with its implementation, its key application areas, and its potential for future advancements. Moreover, a bibliometric analysis was conducted to examine the focus areas of existing studies in the literature, observe how research has developed over time and identify key contributions and emerging trends in DT applications within the construction industry. This literature review defined a framework by identifying the benefits of DT, potential challenges and its primary application areas in the construction phase. In the second section, the study reviews the literature on productivity. Initially, the study examines the concept and definition of productivity, followed by an analysis of its significance and current state within the construction industry. It also discusses the possible reasons behind the insufficient improvement in productivity within the sector. Finally, the study identifies and provides a detailed explanation of the key factors influencing productivity during the construction phase. Furthermore, an analysis was conducted to examine research on productivity and DT, highlighting key focus areas and emerging trends in the field. Through this literature review, the key factors influencing productivity during the construction phase were identified and defined to include it into the next stages of the research. A literature review was conducted to explore DT technology's potential impact on construction productivity factors in order to integrate it into the research survey for assessment. As a result of the review, a survey was designed based on the insights gained from the existing body of knowledge. While the literature review section in the study presents a detailed examination of the relevant factors and the existing body of knowledge, Table 3.1 provides a summary of the key factors employed in the study.

Table 3.1 : Summary of factors identified in the literature review.

Variable	Factors	Subcategories
Factors Affecting Productivity During the Construction Phase	Labor	Skill, Training, Motivation
	Work Site	Site layout, Site location
	Management System	Cost/Time/Quality/Material&Equipment management, Desicion making ability, Organizational methods
	Industry Environment	Financial uncertainties, Regulatory changes
	Design Related Issues	Constructability, Inaccuracies in drawings
	Climate	Adverse weather conditions
	Communication	Misunderstanding, Commmunication barriers
The Benefits of DT	Real Time Digital Representation	
	Remote Monitoring	
	Resource Management	
	Safety Management	
	Risk Management	
	Collaboration with Autonomous Robots	
	Waste Reduction	
	Predictive Decision Making	
	Time And Cost Management	
	Communication And Collaboration	

Table 3.1 (continued) : Summary of factors identified in the literature review.

Variable	Factors	Subcategories
Challenges in Implementing DT	Adaptability	
	Data Integration	
	Data Management	
	High-Fidelity Model	
	Interoperability	
	Operation Cost	
	Cybersecurity and Privacy	
	Skill and Training	
	User Interface	
Key Applications of DT During the Construction Phase	Workforce Oversight	
	Material&Equipment Management	
	Site Monitoring	
	Optimization of Time and Cost	
	Enhanced Decision Making Processes	
	Integration with Emerging Technologies	
	Comprehensive Participation	

3.2 Survey

In this study, a questionnaire was designed and conducted among industry experts to assess the effectiveness of DT in improving factors that impact construction productivity in the construction stage. A pilot study was first conducted to assess the clarity and comprehensibility of the survey. El-Gohary and Aziz (2014) conducted their pilot study with five participants, while Parekh and Mitchell (2024) included seven participants in theirs. Following a similar approach, a pilot survey was conducted with a sample of eight participants to test the clarity and effectiveness of the questionnaire. Based on the feedback obtained, a number of changes were made to enhance readability and comprehension in response. These included revising questions in clearer, more exact language, giving detailed definitions and adding extra explanations where needed. As a result of this process, the final version of the survey was developed. An online survey platform Google Forms was utilized to gather data from participants. The study targeted construction industry professionals, including project managers, engineers, architects, and specialists. Participants were asked to rate the survey statements using a 5-point Likert scale, where 1 represented not effective and 5 indicated extremely effective. The survey began with questions regarding participants' demographic information, obtaining data on gender, age, education level, profession, years of experience, employing organization, and their role within the organization. Following the demographic section, two questions related to DT were included to assess participants' awareness of the technology and whether they had any prior experience using it. After the first sections, the survey continued with questions relevant to the topic. First, participants asked to assess factors affecting productivity during the construction phase. Then they evaluated how frequently these factors occur in construction projects. Next, the survey explored the potential impact of DT by asking how its implementation during the construction phase could influence the occurrence of these productivity related factors. Subsequently, participants rated the benefits of DT in the construction sector. A similar assessment was conducted for challenges associated with DT implementation and its key application areas in construction. Finally, the survey concluded with a summary question, asking participants to express their views on the overall effectiveness of DT in enhancing productivity during the construction phase of construction projects.

3.3 Data Collection

The survey was shared online through direct invitations to construction professionals, and LinkedIn was also used to reach more participants and support its distribution. Data was collected from participants using Google Forms. The survey remained open for responses over a period of seven weeks. A total of 76 responses were collected. All responses considered valid and included in the analysis, resulting in the inclusion of 100% of the provided answers in the survey. The collected data was analyzed using Statistical Package for Social Sciences (SPSS) v.29 software.

3.4 Data Analysis

To analyze the collected data, a series of statistical methods were employed. Descriptive statistics, including mean, median, mode and standard deviation, were utilized to summarize participant responses. To ensure the reliability of the data, Cronbach’s alpha reliability test was conducted. Next, the normality of the data was assessed using multiple methods, including histogram analysis, Skewness-Kurtosis values, the Kolmogorov-Smirnov test, and the coefficient of variation. Once normality was confirmed, Pearson’s correlation test was performed to examine the presence of a significant linear relationship between variables. Afterwards, independent samples t-tests were executed to compare perceptions of DT between users and non-users. Additionally, one-way ANOVA was performed to examine whether experience levels influenced perceptions of DT’s benefits, challenges, and major applications. When ANOVA results indicated statistical significance, post-hoc tests, such as Tukey’s HSD and Gabriel’s Test, were applied to determine significant differences among experience groups.

4. FINDINGS AND DATA ANALYSIS

4.1 Demographic Information of Participants

To gain a better understanding of the participants in terms of gender, age, education and occupation, seven demographic questions were asked to respondents. In the following step, two questions were presented to evaluate their understanding of digital twin (DT). All 76 participants' responses were considered, leading to a participation rate of 100%. Table 4.1 provides an overview of the survey participants' demographics. The number of female and male participants is nearly equal, with 54% being female and 46% male. In terms of age groups, the majority of participants, 54 individuals with 71%, fall within the 25-34 age range. This is followed by the 35-44 age group, which comprises nine participants, with 12%. Seven participants, making up 9%, belong to the 18-24 age group. Three participants each, representing 4%, are in the 45-54 and 55-64 age ranges. There are no participants over the age of 64. The majority of the participants consist of young people, which may be due to the fact that they are more active on the internet and related sharing networks. Looking at the educational background, the majority of respondents, 70% with 53 individuals, hold a bachelor's degree. 21 participants, 28%, have a master's degree, while two participants, accounting for 2%, hold a doctoral degree. In terms of profession, the majority of survey experts are architects, with 55 individuals, accounting for 72% of the group. Civil engineers make up 13%, with 10 participants in this category. Three respondents, 4%, are mechanical engineers, while another three, also 4%, work as project managers. No participants identified as computer/software engineers. Respondents who selected “the others” option in the profession question include an electronics engineer, an urban planner, a contractor, an electrical engineer and an architect with a dual degree in civil engineering. The participants' experience levels vary across different ranges. Most of them, 44 individuals (58%), have 2-5 years of experience. 14 participants (18%) have less than two years of experience, while nine (12%) have more than 15 years.

Table 4.1 : Overview of the survey participants' demographics.

Demographic Variable		Number of Responses	Responses(%)
Gender	Female	41	54%
	Male	35	46%
Age	18-24	7	9%
	25-34	54	71%
	35-44	9	12%
	45-54	3	4%
	55-64	3	4%
	> 64	-	-
Education Degree	Bachelor	53	70%
	Master	21	28%
	Doctorate	2	2%
Profession	Architect	55	72%
	Civil Engineer	10	13%
	Mechanical Engineer	3	4%
	Computer/Software Engineer	-	-
	Project Manager	3	4%
	Other	5	7%
Experience	< 2 years	14	18%
	2-5 years	44	58%
	6-10 years	4	5%
	11-15 years	5	7%
	> 15 years	9	12%
Organization	Architecture Office	33	43%
	Contracting Company	21	28%
	Consulting Firm	5	7%
	Quality Control&Inspection Company	4	5%
	Academia	1	1%
	Other	12	16%

Table 4.1 (continued) : Overview of the survey participants' demographics.

Demographic Variable		Number of Responses	Responses(%)
Role	Design Architect/Engineer	49	65%
	Site Manager	7	9%
	Senior Manager	5	7%
	Consultant	2	3%
	Academic	1	1%
	Other	12	15%
Informed about the DT	Yes	28	37%
	No	48	63%
DT User	Yes	8	11%
	No	68	89%
	Total	76	100%

Five participants (7%) fall within the 11-15 year range, and four (5%) have 6-10 years of experience. The respondents work in various types of organizations. The largest group, 33 individuals (43%), are employed in architecture offices, followed by 21 participants (28%) working in contracting companies. Five people (7%) are part of consulting firms, while four (5%) work in quality control and inspection companies. Only one participant (1%) is from academia. Among the respondents working outside the specified organization, six are in the public sector, two in an airline company, and one each in an investment firm, an energy company, a manufacturing firm and a portfolio company. The survey experts occupy different roles in their organizations. The majority, 49 individuals (65%), work as design architects or engineers. Seven participants (9%) serve as site managers, while five (7%) hold senior management positions. Two people (3%) work as consultants, and one (1%) is in an academic role. Out of the 11 respondents who chose “the others” for their role, the positions include a proposal architect, an avionics design engineer, an interior designer, a specialist, a business development specialist, four project managers, a company owner, a site architect, and an analyst. In summary, the participant profile reveals that the majority of respondents are architects (72%), primarily between the ages of 25 and 34 (71%). Most of them are highly educated, with 70% holding a bachelor's degree and 25% a master's degree. Regarding professional experience, approximately 42% have 2–5 years, while around 32% have less than 2 years of experience. The respondents predominantly work in architectural offices as design professionals. Aside from the demographics, when asked about their knowledge of DT technology, 28 participants (37%) stated they are aware of it, whereas the other 48 respondents (63%) are not familiar with the concept. Of the 28 people informed about the DT technology, eight (11%) have had the opportunity to use this technology before. Among the 76 participants, 68 (89%) have never used DT technology. The details are shown in Table 4.2.

Table 4.2 : Overview of the DT users' demographics.

No	DT User	Education Degree	Profession	Experience
1	Yes	Master	Architect	2-5 years
2	Yes	Master	Architect& Civil Engineer	2-5 years
3	Yes	Master	Project Manager	> 15 years
4	Yes	Bachelor	Architect	< 2 years
5	Yes	Bachelor	Architect	2-5 years
6	Yes	Master	Architect	2-5 years
7	Yes	Master	Mechanical Engineer	2-5 years
8	Yes	Master	Architect	2-5 years

An important feature is that the experience of these eight individuals typically falls within the 2-5 year span. It can show that younger professionals are more involved with such innovations within the construction industry. Moreover, this may suggest that although their experience is not at an advanced level, they have a background in using important technologies. Also 75% of the DT users in the questionnaire are architects, with a majority holding a master's degree.

4.2 Statistical Analysis of Data

The literature research identified the 18 factors impacting productivity during the construction phase. In total, these subcategories identified under seven main categories. Afterwards survey participants were asked about the impact level of these factors. Then, they were questioned about the frequency of their encounters with these factors during construction. Lastly, regarding DT technology and productivity, they were asked how these factors might have been influenced if a DT had been employed during the project's construction phase. Participants were requested to reply using a five-point Likert scale. Moreover, related to DT technology, through a literature review the benefits of DT were identified, and the relevant factors were listed. Participants then rated these factors using a five-point Likert scale. The same process was applied to challenges in implementing DT in construction and key applications of DT during the construction phase. The survey was concluded with a final question evaluating the effectiveness of DT in improving productivity during the construction phase. Based on all of this information, for a descriptive analysis, Table 4.3 was generated showcasing essential statistical metrics such as mean, median, mode and standard deviation for each factor. The factors are arranged from the highest mean to the lowest. According to the table, participants ranked labor (i.e., 4,14) as the most influential factor impacting productivity during the construction phase. The management system (i.e., 4,11) positioned second. Although the management system comes second, its mean value is closely aligned with the labor factor. This might indicate that participants consider it as important as the most impactful factor (i.e., there is no statistical significance). Supporting this, labor related factors are frequently emphasized in the literature as the most significant aspect on construction productivity (Alzubi et al., 2023; Rathnayake and Middleton, 2023; Lee et al., 2023). Moreover, some researchers claim that the management approach is ranked as having the highest impact on construction (Durdyev et al., 2018; El-Gohary and Aziz, 2014; Ghoddousi and Hosseini, 2012). In line with the survey results, these two factors hold similar rankings in the literature as the most effective ones. Design related issues (i.e., 3,72) came in third place while the work site (i.e., 3,57) and industry environment (i.e., 3,54) factors stand 4th and 5th. Alzubi et al. (2023) state that aspects related to the construction site are ranked immediately behind the management system. Alabdali et al. (2022) claim that construction productivity is most affected by incomplete drawings and missing elements, followed by inadequate site circumstances and management. However, survey results assign less importance to these factors, in the findings these are found to be less influential. Participants identified communication (i.e., 3,43) and climate (i.e., 3,25) as the least impactful factors. Nevertheless, although they are in last place, their average values are not considerably low, since both exceed 3. Additionally, the mean values of the four lowest positioned factors are closely aligned. This may suggest that respondents consider minimal differentiation in the importance of these four factors.

Table 4.3 : Descriptive survey statistics.

Variables		Mean	Median	Mode	Std Dev.	N
Factors' Impact on Productivity During Construction	Labor	4,14	4,33	5,00	,750	76
	Management System	4,11	4,33	4,67	,695	76
	Design Related Issues	3,72	4,00	4,00	,984	76
	Work Site	3,57	3,50	3,00	,877	76
	Industry Environment	3,54	3,50	4,00	,944	76
	Communication	3,43	3,50	4,00	,941	76
	Climate	3,25	3,00	3,00	1,047	76
Occurrence Frequency of Factors	Labor	3,85	4,00	4,00	,850	76
	Management System	3,60	3,58	3,67	,882	76
	Design Related Issues	3,31	3,50	3,50	1,052	76
	Industry Environment	3,20	3,00	3,00	,966	76
	Communication	3,05	3,00	2,00	1,144	76
	Work Site	2,96	3,00	2,00	1,032	76
	Climate	2,95	3,00	2,00	1,253	76
The Level of Influence on These Factors If DT Were Used	Design Related Issues	3,84	4,00	4,00	,956	76
	Management System	3,77	3,92	4,00	,784	76
	Work Site	3,26	3,00	3,00	,978	76
	Communication	3,11	3,00	3,00	1,293	76
	Labor	3,02	3,00	3,00	1,012	76
	Industry Environment	2,56	2,50	2,00	1,080	76
	Climate	2,37	2,00	1,00	1,295	76
The Benefits of DT	Remote Monitoring	4,32	5,00	5,00	,867	76
	Time And Cost Management	4,30	5,00	5,00	,848	76
	Resource Management	4,18	4,00	5,00	,843	76
	Real Time Digital Representation	4,17	4,00	5,00	,985	76
	Predictive Decision Making	4,10	5,00	5,00	,974	76
	Risk Management	4,09	4,00	4,00	,819	76
	Collaboration with Autonomous Robots	3,96	4,00	4,00	1,025	76
	Communication and Collaboration	3,89	4,00	4,00	,932	76
	Waste Reduction	3,68	4,00	4,00	1,022	76
	Safety Management	3,64	4,00	4,00	,975	76

Table 4.3 (continued) : Descriptive survey statistics.

Variables		Mean	Median	Mode	Std Dev.	N
Challenges in Implementing DT	Skill and Training	3,54	4,00	5,00	1,259	76
	User Interface	3,20	3,00	4,00	1,118	76
	Cybersecurity and Privacy	3,20	3,00	4,00	1,244	76
	Operation Cost	3,20	3,00	2,00	1,276	76
	Adaptability	2,99	3,00	3,00	1,089	76
	Interoperability	2,89	3,00	3,00	1,138	76
	Data Integration	2,83	3,00	2,00	1,248	76
	Data Management	2,82	3,00	2,00	1,262	76
	High-Fidelity Model	2,82	3,00	2,00	1,283	76
Key Applications of DT During the Construction Phase	Optimization of Time and Cost	4,17	4,00	5,00	,971	76
	Integration with Emerging Technologies	4,09	4,00	5,00	,882	76
	Site Monitoring	4,07	4,00	5,00	1,024	76
	Enhanced Decision Making Processes	4,03	4,00	5,00	1,006	76
	Material&Equipment Management	4,00	4,00	5,00	,924	76
	Comprehensive Participation	3,84	4,00	5,00	1,020	76
	Workforce Oversight	3,51	4,00	3,00	1,026	76
The effectiveness of DT in improving productivity during construction phase		4,09	4,00	4,00	,636	76

Alongside the claims of Alzubi et al. (2023), Hasan et al. (2018), and Rivas et al. (2011), climate was listed last in the outcomes of the survey. Nonetheless, unlike the survey results, Rathnayake and Middleton (2023) emphasize that the climate factor has a more significant impact. Some researchers indicate that the influence of the communication factor on productivity is regarded as more significant than what the survey findings show (Mehta et al., 2022; Naoum, 2016; Jarkas and Bitar, 2012). This may be due to participants' insufficient understanding of the critical role of communication in the construction sector. The average mean values for the factors' impact on productivity during construction and their occurrence frequency exhibit a similar ranking, with the top three factors being labor, management system and design related issues. These three are the both the most influential and the most widespread factors according to survey results. Even though Rathnayake and Middleton (2023) identify labor, equipment & technology and construction site factors as the three most frequently cited factors affecting construction productivity, the survey data claim it is labor, management system and design related issues. This difference may be due to the study of Rathnayake and Middleton (2023) being based on a systematic review that integrates findings from diverse cultural contexts, whereas our survey reflects a more localized perspective. When comparing the occurrence frequency and factors affecting productivity results, the work site (i.e., 2,96) factor falls from 4th to 6th position, whereas the industry environment (i.e., 3,20) rises from 5th to 4th in the occurrence frequency. Based on the responses, while the impact of the work site factor on efficiency was reported to be high, its frequency of occurrence was noted to be low. On the other hand, the industry environment had a higher frequency of occurrence despite having a smaller effect. Communication (i.e., 3,05) advances from 6th to 5th place, while climate (i.e., 2,95) stays at the bottom. According to respondents, in projects, the occurrence frequency of the communication factor is higher compared to its influence. Contrary to the survey results Hasan et al. (2018) indicate the most common factor affecting construction productivity is material shortages, followed by inadequate supervision and skill gaps. Despite the top three, other attributes they listed in descending order in line with the survey findings: incomplete drawings and specifications, poor communication, inefficient site layout and adverse weather.

In the context of the level of influence on these factors if DT were used, a shift in the mean values is observed. Despite labor being the most influential and frequently encountered factor in productivity, its potential impact on productivity when DT technology is applied is not rated as highly. With a mean value of 3,02 it ranks 5th according to the participants' average. In support of this, workforce oversight, associated with the labor factor, was identified as the lowest ranked area among the key application areas of DT in the construction phase. According to the participants, DT technology may not be expected to have a strong influence on labor. Respondents perceive that design related issues would be the most impacted factor by the use of DT, with a mean value of 3,84. However, despite agreeing this, when asked about the key application area for DT, they ranked comprehensive participation, which facilitates process integration and simplifies drawing error resolution, second to last. Instead, they prioritized optimization of time and cost as the most crucial application area. The management system aspect stands in second place, having a mean value of 3,77. Among the factors affecting productivity in the construction industry, considering both their impact and frequency of occurrence, the management system was identified as the second most critical factor too. A comparison of the responses can show that participants consider management system factor highly influential on productivity and believe that the use of DT technology may offer considerable benefits and lead to notable improvements in this area. Work site (i.e., 3,26) holds the third position in the table. While the work site was not among the most frequently observed factors affecting productivity, its impact level ranked fourth when it was asked. Despite this, participants believed that DT technologies might have a high level of influence on this factor, placing it third in the rankings. This can suggest that they may consider DT effective in improving site planning. Although the communication places 4th for this question, participants may show uncertainty regarding the influence of DT on communication, as evidenced by a mean value of 3,11. Communication was already not considered by participants as a highly influential or frequently observed factor. Similarly, when asked in detail about survey experts' perception of DT, communication related variables also ranked towards the bottom in both the advantages of DT (communication and collaboration) and the key application areas (comprehensive participation). The industry environment and climate factors are listed 6th and 7th, respectively, with mean values of 2,56 and 2,37. Respondents might consider that these two factors would not be significantly affected by DT, as shown by their lower mean ratings. Since these are external factors, lower mean scores were expected.

Overall, when participants were asked about the factors affecting productivity and their frequency of occurrence during the construction phase, the top three factors they identified were the same: labor, management system and design-related issues. In contrast, when asked which factors would be most influenced by the use of DT technologies, two of these three factors (management system and design related issues) were again ranked in the top three. This may indicate that the use of DT technologies could be a highly effective solution for addressing the most common and impactful factors reducing productivity during the construction phase.

Upon reaching the questions related to the perception of DT, when examining the benefits of DT, participants listed remote monitoring (i.e., 4,32) as the most significant benefit, closely followed by time and cost management (i.e., 4,30), with almost identical values. Resource management (i.e., 4,18) comes in third, while real time digital representation (i.e., 4,17) ranks 4th, nearly equal to the third factor. Predictive decision making comes 5th (i.e., 4,10) with risk management (i.e., 4,09) just behind. Since the mean values of the first six benefits are all greater than the value of 4, it can be concluded that participants regard the benefits of DT as highly valuable. In the survey results, schedule optimization and predictive maintenance, which received high scores, are also described by Hu et al. (2022) as advanced contributions of DT technology for the construction industry. The two final benefits are waste reduction (i.e., 3,68) and safety management (i.e., 3,64). Their average values are not low, even though they place in the bottom two. The reason waste reduction is in the lower ranks could be that sustainability is not considered a high priority among the participants. Likewise, the positioning of safety management at the last place may be due to the lack of sufficient attention given to this factor during the construction phase. Opposed to questionnaire results, Moshood et al. (2024) highlight the vitality of DT in sustainability by claiming that DT will be essential to creating sustainable urban settings in the future. Similarly, Teizer et al. (2022) emphasize the importance of the integration of DT technology in construction safety in contrast to participants' opinions.

In the analysis of the challenges in implementing DT, a score of 5 would typically indicate a high level of difficulty. Nonetheless, the participants' scores for these challenges were not particularly high. This might imply that respondents generally believe the implementation of DT does not involve considerable difficulties. The highest ranked challenge, skill and training, received a mean score of 3,54. Parallel to the survey results, Jiao et al. (2024) state that the role of each stakeholder cannot be considered in isolation, as DT implementation requires collaboration across various professions and disciplines. Consequently, ensuring that everyone is skilled in this area may emerge as one of the key challenges that may be encountered. The challenges of user interface, cybersecurity & privacy, and operational costs, positioned second, third and fourth respectively, all share the same mean value of 3,20. An examination of the three main challenges identified by participants may show widespread worries about data privacy and usability of the technology. Adaptability (i.e., 2,99) and interoperability (i.e., 2,89) are listed as the 5th and 6th challenges in the table. Given that the mean values are below 3, it can be concluded that the experts participating in the survey do not regard these two challenges as major concerns. The challenges holding the last three positions are data integration (i.e., 2,83), data management (i.e., 2,82) and high-fidelity models (i.e., 2,82). Participants perceive these ones as less likely to cause significant issues. Technological advancements in data processing and modeling may have contributed to participants' confidence in these areas. Nevertheless, while participants do not view the data management challenge as a major obstacle, Jiao et al. (2024) assert that the accessibility of new data sets, data security and data analysis during the DT implementation process make the data management system a primary barrier at the project level. When asked in the survey whether they had any general comments about DT technology, a few participants expressed concerns regarding its challenges. One respondent expressed concerns regarding the current applicability of DT, because it is still in an early stage of development and adoption in the country. Another pointed out that a significant obstacle is the companies' reluctance to share data in the industry. The third concern focused on the possibly high initial investment cost of DT, which would limit its use in small scale projects. The fact that the participants who provided general comments mostly focused on its challenges may indicate that, despite its increasing popularity, people may still have uncertainties and doubts about its integration and adoption.

According to respondents, during the construction phase, the main priority among the key applications of DT is time and cost optimization (i.e., 4,17). This aligns with respondents’ earlier ranking of time and cost management as the second most significant benefit of DT. This may be highlighting their strong belief in its potential advantage. Integration with emerging technologies (i.e., 4,09) follows closely in second place, which might reflect the growing importance of technological advancements in the industry. Additionally, site monitoring (i.e., 4,07) is located third, emphasizing the significance of remote monitoring, which was previously identified by respondents as the most valuable benefit of DT. Yang et al. (2024) explain DT integrates with advanced technologies and their implementation in buildings enables real time monitoring. This relationship is also evident in the survey findings where factors ranked second and third respectively, with similar values. Enhanced decision making processes (i.e., 4,03) ranks 4th, while material & equipment management (i.e., 4,00) comes in 5th. In response to the question about the benefits of DT, decision making processes also ranked in the middle according to the participants' answers. Nonetheless Yang et al. (2024) examines DT systems' potential to revolutionize decision making in the construction industry. The last two factors, comprehensive participation (i.e., 3,84) and workforce oversight (i.e., 3,51), listed the lowest. Comprehensive participation is related to communication and it was also placed low in the factors affecting productivity. While the researchers (Hasan et al., 2018; Zhang et al., 2024; Yang et al., 2024) highlight its importance, survey respondents did not view it as a highly effective application of DT. This may stem from inadequate focus on task distribution among stakeholders and an underestimate of its significance for promoting a collaborative construction process. Jiao et al. (2024) mention that one of the biggest problems the sector faces is the failure to finish a project on schedule, which is mostly caused by the combined activities and tasks of the owner, contractor, and other stakeholders. That's why researchers suggest these two factors should not be considered too separately, as they can be interconnected. However, in the survey results optimization of time and cost ranks first among key application areas, while comprehensive participation is the second lowest. Furthermore, even though labor was previously identified as the most influential factor on productivity, it did not receive a high rating in terms of the areas of application that DT technology would bring. This might suggest that participants may not perceive DT as greatly impacting labor.

With a mean score of 4,09, the effectiveness of DT in enhancing productivity during the construction stage was firmly confirmed by participants. This may indicate that they regard the DT system as a valuable technology for boosting productivity in the construction sector.

Eight participants in the survey indicated that they had previous experience with DT technology. To assess their perspectives, the mean values of their Likert scale responses were analyzed across five categories: the influence of DT on factors affecting productivity if applied, the benefits of DT, challenges in implementing DT, key applications of DT during the construction phase, and the effectiveness of DT in improving productivity during the construction phase. Firstly the influence of DT on factors affecting productivity was analyzed. The ranking of factors remained consistent with the overall dataset, except for a position swap between communication and worksite factors. Participants ranked communication third and worksite fourth, reversing their order in the overall results. The mean values for each factor were: design related issues (i.e., 4.50), management system (i.e., 4.02), communication (i.e., 3.56), worksite (i.e., 3.44), labor (i.e., 3.21), industry environment (i.e., 2.50), and climate (i.e., 2.50). When comparing the results with the general evaluation, the mean value for design related issues is significantly higher. Additionally, management system and communication factors also have higher mean values, indicating that participants with DT experience believe these factors would be more impacted by DT implementation. The remaining factors show only minor differences. When examining the analysis of the benefits of DT, real time digital representation was rated significantly higher, indicating a stronger emphasis on its importance according to DT users. They perceive it as the most valuable benefit of DT. Meanwhile, remote monitoring, time and cost management, resource management, and risk management were also rated higher, but with minor differences. In contrast, predictive decision making and waste reduction received notably lower ratings. DT users might not view these advantages as transformative and critical as others. The remaining factors showed minimal variation and remained almost the same. The mean values for each factor were as follows: real time digital representation (i.e., 4.50), remote monitoring (i.e., 4.50), time and cost management (i.e., 4.50), resource management (i.e., 4.25), risk management (i.e., 4.25), communication and collaboration (i.e., 4.00), collaboration with autonomous robots (i.e., 4.00), safety management (i.e., 3.75), predictive decision making (i.e., 3.75), and waste reduction (i.e., 2.88). Third, the challenges in implementing DT were examined. Interoperability, data integration, data management, and high fidelity model received dramatically higher ratings from DT users. They regard these challenges to be more complex compared to respondents who have not used DT before. Whereas, skill and training and user interface were also rated higher, but with only slight differences. Although these two received higher ratings, factors still do not rank among the top three challenges identified by DT users. Conversely, cybersecurity and privacy were rated notably lower. DT users do not consider it as a significant obstacle compared to non DT users. The remaining variables showed little shift and remained mostly unchanged. The mean values for each factor were as follows: skill and training requirements (i.e., 3.88), high-fidelity modeling (i.e., 3.63), data integration (i.e., 3.50), user interface (i.e., 3.50), integration with other technologies (i.e., 3.25), data management (i.e., 3.13), adaptability (i.e., 3.13), operational cost (i.e., 3.00), and cybersecurity and privacy (i.e., 2.75). In the analysis of DT's key application during the construction stage, comprehensive participation and workforce oversight received notably higher ratings from DT users. This might show that their familiarity with DT on project coordination, labor tracking and stakeholder management with DT contributes to their more positive assessment of these application areas. Meanwhile, optimization of time and cost, site monitoring, and material & equipment management were also rated higher, but with only slight differences. The other factors exhibited minimal variation. The average ratings for each factor were as follows: optimization of time and cost (i.e., 4.50), site monitoring (i.e., 4.38), material and equipment management (i.e., 4.25), comprehensive participation (i.e., 4.25), enhanced decision making process (i.e., 4.13), integration with emerging technologies (i.e., 4.13), and workforce oversight (i.e., 4.00). When examining the question regarding the effectiveness of DT in improving productivity during the construction phase, it was found that although the overall mean value was 4.09, DT users rated it slightly higher, with a mean of 4.38. According to DT users and with a lower degree all participants, DT is perceived as highly effective.

4.2.1 Reliability analysis

A reliability analysis was performed using Cronbach's Alpha to evaluate the internal consistency of the responses provided in the survey. A high Cronbach's Alpha value, ranging from 0 to 1, indicates that the factors or questions being tested are highly consistent with each other. A Cronbach's Alpha of 0.9 or higher indicates excellent reliability, while a value between 0.8 and 0.9 reflects good consistency. An Alpha between 0.7 and 0.8 suggests acceptable reliability. Table 4.4 presents Cronbach's Alpha values for the questions included in the survey. The Cronbach's Alpha values for the first three questions exceed 0.9, signifying excellent reliability, while for the last three questions, the values surpass 0.8, demonstrating good consistency. Generally the number of statements in the scale also influences Cronbach’s alpha, as the number of items increases alpha tends to rise. A Cronbach’s alpha above 0.9 may be attributed to a large number of statements, making a high alpha expected. Overall, the survey exhibits high reliability based on these Cronbach's Alpha scores.

Table 4.4 : Cronbach's alpha values.

Variables	Number of Statements	Cronbach's Alpha Value
Factors' Impact on Productivity During Construction	18	,932
Occurrence Frequency of Factors	18	,913
The Level of Influence on These Factors If DT Were Used	18	,909
The Benefits of DT	10	,870
Challenges in Implementing DT	9	,896
Key Applications of DT During the Construction Phase	7	,833

4.2.2 Normal distribution analysis

A normality test was conducted to assess whether the sample data followed a normal distribution, guiding the selection of further analyses such as correlation analysis, independent samples t-test and one-way ANOVA. Tabachnick and Fidell (2013) state that Skewness-Kurtosis values need to fall within the range of +1.5 and -1.5. Orcan (2020) mentions assessing normality solely based on Skewness-Kurtosis values is unreliable; therefore, they should not be used as the only criteria. The normal distribution is a symmetric probability distribution with a bell shaped curve that shows that data closer to the mean occur more often than data far away (Maity and Saha 2022). Yap and Sim, (2011) claim graphical techniques can be helpful in determining if sample data is normal, but they cannot offer recognized, final proof that the normal assumption is true. Therefore they recommend the Kolmogorov-Smirnov test which evaluates normality, where a p-value above 0.05 indicates that the null hypothesis is not rejected, suggesting the data follows a normal distribution. Moreover the coefficient of variation serves as a valuable metric for assessing scale reliability by evaluating the degree to which measurements are distributed around a central value (Seeletse and Miyambu, 2017; Thangjai et al., 2021). Koch and Link (1971) specifically suggest that a coefficient of variation lower than 0.50 reinforces the assumption of normality whereas Hayya et al. (1975) claim 0.39. Overall, several techniques are employed in data analysis to determine whether a data collection is normally distributed, including Skewness-Kurtosis values, bell curve shape of the histogram graph, Kolmogorov-Smirnov test result and coefficient of variation. In this study, datasets that satisfied at least half of the mentioned techniques were assumed to exhibit a normal distribution.

As a first step, the skewness and kurtosis values of the variables were assessed to determine whether they lay between +1.5 and -1.5. Since the skewness and kurtosis values for all variables fall within the range of +1.5 to -1.5, it can be concluded that the data have a normal distribution according to the values. In the second step, the histogram graphs were examined. Figure 4.1 illustrates the histogram charts of the variables.

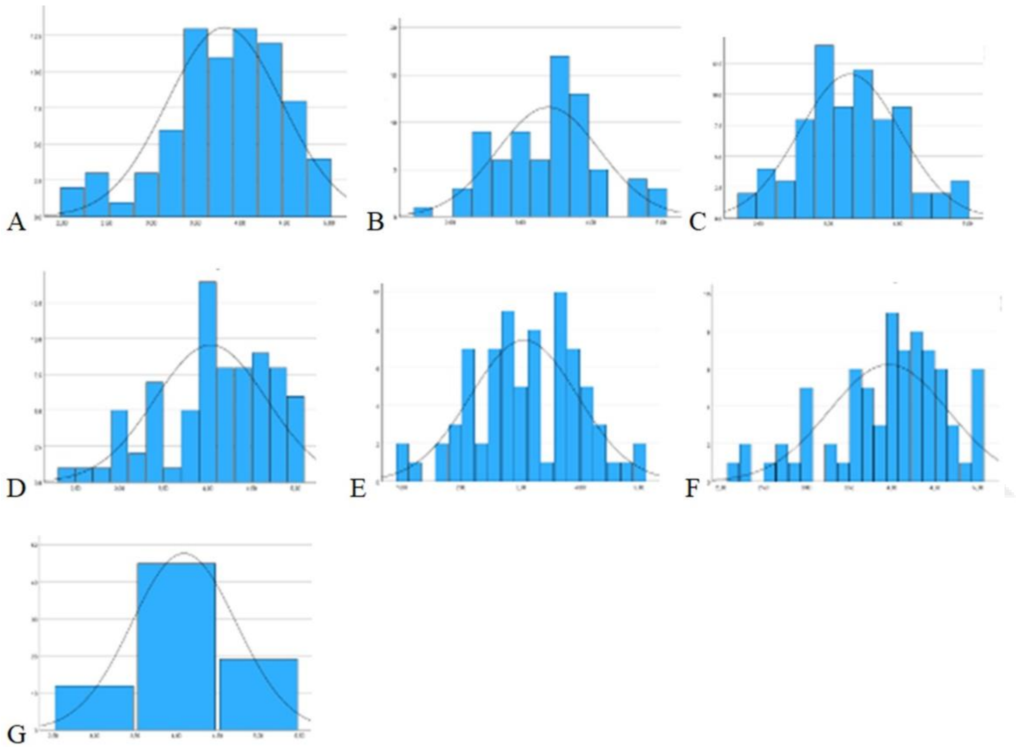

Figure 4.1 : Histogram graphs of the variables.

Based on the histograms, graphs B (occurrence frequency of factors), C (the level of influence on these factors if DT were used), E (challenges in implementing DT) and G (the effectiveness of DT in improving productivity during construction phase) demonstrate a bell shaped curve representing a normal distribution, whereas graphs A (factors' impact on productivity during construction) , D (the benefits of DT) and F (key applications of DT during the construction phase) do not indicate normality when evaluated only through histograms. Since there are 76 participants in the survey, the Kolmogorov-Smirnov normality test which is recommended for sample sizes exceeding 50, was conducted as a third step. As a result, the p-values of A (factors' impact on productivity during construction), B (occurrence frequency of factors), C (the level of influence on these factors if DT were used), E (challenges in implementing DT) variables were found to be greater than 0.05, indicating that they meet the normality assumption. However, variables D (the benefits of DT), F (key applications of DT during the construction phase) and G (the effectiveness of DT in improving productivity during construction phase) did not satisfy this criterion, as their p-values were below 0.05. Lastly, the coefficient of variation was computed for each factor in the survey data. Since the coefficients for all variables were found to be less than 0.50, it may be concluded that the survey data satisfied the normality assumption. Considering all these results, while some variables (B, C, E) were found to meet all the conditions, others meet three of the conditions (A, G), and some satisfied half of the criteria (D, F). Therefore, the overall data was assumed to follow a normal distribution. Table 4.5 presents a summary of the normality analysis conducted in this study. Thus, the analyses of correlation, independent samples t-test, and ANOVA were conducted using methods suitable for normally distributed data.

Table 4.5 : Normality test of the survey data.

No	Variables	Descriptive	Results	
A.	Factors' Impact on Productivity During Construction	Skewness&Kurtosis	-,613	,215
		Histogram graphic	Not bell curve	
		Kolmogorov-Smirnov	,099	
		Coefficient of variation	0,168	
B.	Occurrence Frequency of Factors	Skewness&Kurtosis	,101	-,153
		Histogram graphic	Bell curve	
		Kolmogorov-Smirnov	,079	
		Coefficient of variation	0,215	
C.	The Level of Influence on These Factors If DT Were Used	Skewness&Kurtosis	,172	-,299
		Histogram graphic	Bell curve	
		Kolmogorov-Smirnov	,200	
		Coefficient of variation	0,218	

Table 4.5 (continued) : Normality test of the survey data.

No	Variables	Descriptive	Results	
D.	The Benefits of DT	Skewness&Kurtosis	-,562	-,335
		Histogram graphic	Not bell curve	
		Kolmogorov-Smirnov	,018	
		Coefficient of variation	0,157	
E.	Challenges in Implementing DT	Skewness&Kurtosis	-,121	-,424
		Histogram graphic	Bell curve	
		Kolmogorov-Smirnov	,167	
		Coefficient of variation	0,296	
F.	Key Applications of DT During the Construction Phase	Skewness&Kurtosis	-,721	,082
		Histogram graphic	Not bell curve	
		Kolmogorov-Smirnov	,001	
		Coefficient of variation	0,175	
G.	The Effectiveness of DT in Improving Productivity During Construction Phase	Skewness&Kurtosis	-,072	-,480
		Histogram graphic	Bell curve	
		Kolmogorov-Smirnov	,001	
		Coefficient of variation	0,155	

4.2.3 Correlation analysis

In order to assess the relationships between the variables, a Pearson correlation analysis was executed. The correlations were examined under six different categories based on the framework of the study. The Pearson correlation varies between -1 and +1, where a value of 0 signifies the absence of any relationship between the variables. Positive coefficients indicate a direct linear relationship, meaning that as one variable increases, the other also increases. In contrast, negative coefficients reflect an inverse linear relationship, where an increase in one variable corresponds to a decrease in the other. In this study, correlation values higher than 0.60 are accepted as reflecting a strong association between the variables; thus, factors with a correlation value above 0,60 were highlighted in bold in related tables for detailed discussion. Table 4.6 presents the Pearson correlation results for the categories of factors affecting productivity during the construction phase. As shown in the table, all variables exhibit significant correlations at the 0.01 level. Nevertheless, three high level strong positive correlations with coefficients exceeding 0.60 are notable, all of which are significant at the 0.01 level. The first very strong positive correlation is found between the management system and labor factors, with a coefficient of 0.639, which is significant at the 0.01 level. This may indicate that participants who considered the management system to have a significant impact on productivity also perceived labor related factors as important. In their study, Alzubi et al. (2023) found that the workforce factor ranked as the most influential on construction productivity, followed by management. They explain that this relationship can be attributed to the significant influence of management decisions on workers' performance. Parallel to this information survey results show similar relations. Similarly, the second highly significant positive correlation is found between the design related issues and work site factors, with a coefficient of 0.605, which is also significant at the 0.01 level. This may be due to the fact that both factors are related to the quality of planning and efficient workflow. Design related factors, including incomplete or inaccurate drawings may directly affect worksite conditions by causing difficulties in constructability and implementation. Likewise Naoum (2016) highlights, inefficient designs may disrupt worksite operations by complicating construction and causing poor utilization of resources. Therefore, participants who found design related issues important were likely to value the work site factor as well. Lastly, the final high level strong positive correlation in this category is observed between the design related issues and management system factors, with a coefficient of 0.616, again significant at the 0.01 level. Design and management processes can be seen closely interconnected. When management quality improves, design outputs usually improve as well, supporting higher standards and greater productivity rate across the project. Moreover, in well managed projects, design results are generally reliable, accurate and constructible for construction. For this reason we may conclude that participants who rated design related issues as highly influential on productivity also perceived the management system as important. Consistent with the survey findings, Naoum (2016) points out that delays caused by design errors and variations are among the leading factors affecting productivity, underlining the need for a strong management system. Table 4.7 presents the correlation analysis of the occurrence frequency of factors.

Table 4.6 : Correlations between the factors affecting productivity during the construction phase.

Category	Variables	Lbr	Wrk_st	Mngmt_Sys	Indsrt_Env	Dsgn_R_I	Clmt	Commctn
Factors' Impact on Productivity During Construction	Labor	1						
	Work Site	,421**	1					
	Management System	**,639****	,559**	1				
	Industry Environment	,541**	,351**	,496**	1			
	Design Related Issues	,508**	**,605****	**,616****	,572**	1		
	Climate	,458**	,541**	,506**	,421**	,587**	1	
	Communication	,370**	,454**	,491**	,405**	,536**	,547**	1

** Correlation is significant at the 0.01 level.

Table 4.7 : Correlations between occurrence frequency of factors.

Category	Variables	Lbr	Wrk_st	Mngmt_Sys	Indsrt_Env	Dsgn_R_I	Clmt	Commctn
Occurrence Frequency of Factors	Labor	1						
	Work Site	,188	1					
	Management System	,591**	,543**	1				
	Industry Environment	,369**	,439**	,445**	1			
	Design Related Issues	,400**	,340**	,521**	,457**	1		
	Climate	,318**	,571**	,415**	**,625****	,331**	1	
	Communication	,414**	,479**	,544**	,456**	,545**	,462**	1

** Correlation is significant at the 0.01 level.

All correlations are significant at the 0.01 level, except for the worksite and labor correlation, which is not significant with a value of 0.188. Additionally, there is only one highly significant positive correlation exceeding 0.60, found between the climate and industry environment factors, with a coefficient of 0.625, which is significant at the 0.01 level. The results suggest that participants perceive a parallel increase or decrease between the occurrence frequencies of these two external factors, climate and industry environment. According to the respondents, difficulties in the industry environment, such as financial uncertainty and regulatory obstacles, frequently occur with adverse climate conditions. This correlation may be coincidental; however, it is also possible that adverse climate conditions affect the industry environment by creating financial uncertainties within the sector. Extreme weather can cause interruptions to the supply chain, project delays and cost increases, all of which can contribute to an unstable business environment. Table 4.8 illustrates the correlations of participants' evaluations of how these factors would be influenced if DT technologies were applied. All correlations are significant at the 0.01 level, except for the correlation between climate and design related issues, which has a coefficient of 0.254 and significant at the 0.05 level. Two high level strong positive correlations greater than 0.60 are identified. The first is observed between the climate and work site factors, with a coefficient of 0.665, significant at the 0.01 level. Although DT technology cannot control climate conditions, the strong positive correlation between climate and work site factors may suggest that participants considered DT may assist in managing the impact of climate on work site operations rather than the climate itself. In this way, DT might be seen as an effective strategy for reducing the impact of weather conditions on work site performance, even though it cannot change the environment itself. The second high level significant positive correlation is between climate and industry environment factors, with a coefficient of 0.652, significant at the 0.01 level. Even while DT cannot influence the climate itself, this result might indicate that participants suppose DT technology may help the industry with handling the adverse impacts of climate issues such as supply chains and uncertainties. Even though climate was addressed directly in the survey, the strong correlations with both the work site and industry environment factors show that participants may have unintentionally taken climate effects into account when evaluating the question. Table 4.9 provides the correlation results for the benefits of DT.

Table 4.8 : Correlations between the levels of influence on these factors if DT were used.

Category	Variables	Lbr	Wrk_st	Mngmt_Sys	Indsrt_Env	Dsgn_R_I	Clmt	Commctn
The Level of Influence on These Factors If DT Were Used	Labor	1						
	Work Site	,514**	1					
	Management System	,317**	,473**	1				
	Industry Environment	,568**	,547**	,382**	1			
	Design Related Issues	,361**	,487**	,597**	,254*	1		
	Climate	,575**	**,665****	,310**	**,652****	,236*	1	
	Communication	,530**	,485**	,373**	,595**	,397**	,585**	1

* Correlation is significant at the 0.05 level.

** Correlation is significant at the 0.01 level.

Table 4.9 : Correlations between the benefits of DT.

Category	Variables	RealT_D_R	Rmt_Mnt	Rsrc_Mngmt	Sfy_Mngmt	Risk_Mng	Collb_Auto_R	Wst_Red	Prdc_Dcs_M	T&C_ Mngmt	Com_Collb
The Benefits of DT	Real Time Digital Representation	1									
	Remote Monitoring	,545**	1								
	Resource Management	,411**	,484**	1							
	Safety Management	,300**	,481**	,485**	1						
	Risk Management	**,641****	,409**	**,650****	,508**	1					
	Collaboration with Autonomous Robots	,522**	,449**	,409**	,319**	,449**	1				
	Waste Reduction	,253*	,114	,408**	,207	,369**	,382**	1			
	Predictive Decision Making	,481**	,307**	,495**	,278*	,472**	,365**	,543**	1		
	Time And Cost Management	,511**	,430**	**,666****	,293*	,592**	,397**	,373**	,493**	1	
	Communication And Collaboration	,223	,207	,432**	,208	,310**	,177	,440**	,424**	,546**	1

* Correlation is significant at the 0.05 level.

** Correlation is significant at the 0.01 level.

In addition, it includes strong correlations that are significant at the 0.01 and correlation at 0.05 levels, as well as some correlations that are not significant. The first highly strong positive correlation, exceeding 0.60, is identified between risk management and real time digital representation factors (r =,641, p< ,001). Real time digital representation has a high potential to support risk management in projects; therefore, the positive correlation between them could indicate that participants likely perceive these factors as interrelated in this context. Likewise Salem and Dragomir (2023) highlight the relation between them as claiming DT improves risk management by enabling fast planning and forecasting through the integration of real time and historical data. Another high level significant positive correlation is identified between risk management and resource management (r = ,650, p < ,001). Similarly, participants may have viewed a comparable perception regarding the relationship between risk management and resource management. As resources are managed more effectively, associated risks may decrease accordingly. Therefore, the positive correlation between these factors could suggest that respondents believe the advantages of DT in resource management also contribute to its effectiveness in risk management. The last highly strong positive correlation appears between time and cost management and resource management (r = ,666, p < ,001). The strong correlation between them may be explained by the close connection between these areas in the construction phase. Participants who considered resource management valuable could be likely regarded time and cost management as equally important in maximizing project efficiency. In parallel to this, Salem and Dragomir (2023) assert, DT technology can guide resource management by monitoring financial items based on the project's financial plan stored in BIM, allowing for accurate tracking of expenditures across specific budget categories, such as worker salaries and raw material costs. Table 4.10 shows the correlation analysis of the challenges associated with implementing DT. These challenges were found to be highly correlated with each other. The table reports 13 highly strong positive correlations exceeding 0.60, which are all significant at the 0.01 level. It also presents other correlations, some of them are significant at the 0.01 and 0.05 levels, while some of others are not significant.

Table 4.10 : Correlations between the challenges in implementing DT.

Category	Variables	Adpt	Dt_Intg	Dt_Mngt	Hgh_Fd_M	Introprblt	Opr_Cst	Cybsc_Priv	Skll_Trng	Usr_Intfc
Challenges in Implementing DT	Adaptability	1								
	Data Integration	**,685****	1							
	Data Management	**,648****	**,869****	1						
	High-Fidelity Model	,561**	**,730****	**,737****	1					
	Interoperability	**,601****	**,626****	**,655****	**,662****	1				
	Operation Cost	**,626****	,516**	,503**	,495**	**,676****	1			
	Cybersecurity and Privacy	,297**	,263*	,219	,224	,335**	,488**	1		
	Skill and Training	,414**	,407**	,357**	,368**	,431**	,514**	**,621****	1	
	User Interface	,262*	,350**	,375**	,280*	,354**	,311**	,546**	**,674****	1

* Correlation is significant at the 0.05 level.

** Correlation is significant at the 0.01 level.

Among the highly strong correlations identified, the highest three were observed between data integration and data management ($r = ,869$, $p < ,001$), data integration and the high fidelity model ($r = ,730$, $p < ,001$), and data management and the high fidelity model ($r = ,737$, $p < ,001$). Since the effective handling of data integration processes plays a critical role in determining the overall quality of data management, the two variables directly influence each other. Thus participants are likely to have evaluated them in parallel, resulting in very strong positive correlations. As Hosamo et al. (2022) state, data must be properly managed after the integration to guarantee its security, availability, and reliability. Without effective data integration, data management becomes challenging. The other strong correlation between data integration and the high-fidelity model can be explained by the need to combine different types of data during the creation of the model, such as visual information (images, 3D scans) and numerical data (sensor outputs). This process may require effective data integration, which strengthens the relationship between these two variables. Jiang et al. (2021) highlight that, together with a high-fidelity model and data integration, DT greatly enhances the precision and quality of design. Furthermore, the last strong correlation reflects the importance of high quality data management in ensuring the accuracy of the high fidelity model, as the model's performance depends on the data it receives. As Opoku et al. (2024) indicate, building and sustaining high-fidelity models requires the availability and accuracy of the data, which is ensured by effective data management. Table 4.11 displays the correlation analysis of the key applications of DT during the construction phase. The table shows three strong positive correlations above 0.60, significant at the 0.01 level, along with other strong correlations significant at the 0.01 and 0.05 levels, and some non significant correlations. The first very strong positive correlation is between material and equipment management, and site monitoring ($r = ,620$, $p < ,001$). This may indicate that improved control on construction sites might be significantly assisted by the successful integration of DT in material and equipment management. Jiang et al. (2021) point out, effective material management ensures materials meet site needs by tracking supply status, directly impacting site efficiency. Therefore, respondents consider site monitoring and material management to strongly influence each other. Material and equipment management is also strongly and significantly correlated with optimization of time and cost ($r = ,669$, $p < ,001$).

Table 4.11 : Correlations between the key applications of DT during the construction phase.

Category	Variables	Wrkfc_Ov	Mtr_Eq_M	St_Mnt	Opt_T&C	Enh_DcM_P	Int_Emg_Tech	Comp_Pp
Key Applications of DT During the Construction Phase	Workforce Oversight	,1						
	Material and Equipment Management	,408**	1					
	Site Monitoring	,500**	**,620****	1				
	Optimization of Time and Cost	,245*	**,669****	**,605****	1			
	Enhanced Decision Making Processes	,452**	,344**	,490**	,568**	1		
	Integration with Emerging Technologies	,168	,311**	,347**	,417**	,433**	1	
	Comprehensive Participation	,244*	,297**	,380**	,377**	,329**	,579**	1

* Correlation is significant at the 0.05 level.

** Correlation is significant at the 0.01 level.

Effective management of materials and equipment employing DT can contribute to improved project efficiency by reducing time and cost overruns. Similarly Piras et al. (2024) mention, efficient material management through DT allows contractors to track materials in real time, ensuring optimal stock levels and reducing costs related to oversupply or shortages. This finding demonstrates the close relationship between material and equipment management, and the optimization of time and cost, suggesting that better control of resources plays a key role in meeting project timelines and budgets. The last significant strong correlation occurs between site monitoring and optimization of time and cost ($r = ,605$, $p < ,001$). Potential delays or budget overruns can be detected early with site monitoring, by the application of DT, enabling immediate action. As Sabet and Chong (2020) indicate, tracking project progress through visual comparisons of completed work and planned designs helps enhance schedule control and boost time efficiency. Likewise survey experts view these two application areas strongly correlated.

4.2.4 Independent samples t-test analysis

In this study, an independent-samples t-test was conducted to determine whether there is a statistically significant difference between participants with knowledge of DT technology and those without. Participants' answers were examined in seven categories, including factors affecting productivity, their frequency, the potential impact of DT on these factors, the benefits and challenges of DT, key DT applications during construction, and DT's effectiveness in enhancing productivity. The analysis was conducted with a sample of 28 participants informed about DT and 48 participants not informed.

At a 95% confidence interval, no significant differences were found between the two groups regarding factors affecting productivity and their frequency of occurrence, as all p-values were above 0.05. Table 4.12 summarizes the group statistics for the factors affecting productivity, and Table 4.13 shows the results of the independent samples t-test for these factors.

Table 4.12 : Group statistics of the factors affecting productivity in the construction phase.

Variables	Sample Group	N	Mean	Std. Deviation
Labor	Informed about the DT	28	3,94	,780
	Not informed	48	4,26	,715
Work Site	Informed about the DT	28	3,66	,913
	Not informed	48	3,51	,860
Management System	Informed about the DT	28	4,08	,645
	Not informed	48	4,12	,729
Industry Environment	Informed about the DT	28	3,48	,957
	Not informed	48	3,57	,945
Design Related Issues	Informed about the DT	28	3,55	,936
	Not informed	48	3,81	1,008
Climate	Informed about the DT	28	3,10	,916
	Not informed	48	3,33	1,117
Communication	Informed about the DT	28	3,39	,994
	Not informed	48	3,44	,918

Table 4.13 : Independent samples t-test results for the factors affecting productivity in the construction phase.

Variables	Levene's Test for Equality of Variances		T-test for Equality of Means	
	F	Sig.	t	p
Labor	0,228	0,634	-1,799	,076
Work Site	0,226	0,636	0,718	,475
Management System	0,082	0,775	-0,230	,819
Industry Environment	0,052	0,82	-0,402	,689
Design Related Issues	0,201	0,656	-1,108	,272
Climate	1,625	0,206	-0,907	,367
Communication	0,014	0,527	-0,245	,807

In addition, Table 4.14 presents the group statistics for the occurrence frequency of the same factors, while Table 4.15 displays the associated t-test results. This result was expected, as the questions in this section did not directly involve areas where knowledge of DT technology would have an impact. Although an indirect effect could have been possible, the t-test results did not reveal any significant difference.

Table 4.14 : Group statistics for the occurrence frequency of the factors.

Variables	Sample Group	N	Mean	Std. Deviation
Labor	Informed about the DT	28	3,89	,754
	Not informed	48	3,83	,909
Work Site	Informed about the DT	28	2,98	1,067
	Not informed	48	2,95	1,022
Management System	Informed about the DT	28	3,58	,692
	Not informed	48	3,61	,983
Industry Environment	Informed about the DT	28	3,11	,975
	Not informed	48	3,25	,967
Design Related Issues	Informed about the DT	28	3,50	1,009
	Not informed	48	3,20	1,070
Climate	Informed about the DT	28	2,64	1,282
	Not informed	48	3,13	1,213
Communication	Informed about the DT	28	3,13	1,033
	Not informed	48	3,00	1,211

Table 4.15 : Independent samples t-test results for the occurrence frequency of the factors.

Variables	Levene's Test for Equality of Variances		T-test for Equality of Means	
	F	Sig.	t	p
Labor	1,672	0,200	0,327	,372
Work Site	0,014	0,907	0,139	,890
Management System	4,991	0,029	-0,193	,848
Industry Environment	0,254	0,615	-0,619	,538
Design Related Issues	0,680	0,412	1,211	,230
Climate	0,060	0,807	-1,636	,106
Communication	1,016	0,317	0,457	,649

For the question examining the potential impact of DT on these factors, Table 4.16 presents the group statistics while Table 4.17 displays the results of the independent samples t-test assessing this impact.

Table 4.16 : Group statistics for the potential impact of DT on factors.

Variables	Sample Group	N	Mean	Std. Deviation
Labor	Informed about the DT	28	3,26	,899
	Not informed	48	2,88	1,055
Work Site	Informed about the DT	28	3,29	,956
	Not informed	48	3,25	1,000
Management System	Informed about the DT	28	3,92	,634
	Not informed	48	3,68	,854
Industry Environment	Informed about the DT	28	2,57	,997
	Not informed	48	2,55	1,135
Design Related Issues	Informed about the DT	28	4,11	,975
	Not informed	48	3,69	,920
Climate	Informed about the DT	28	2,32	1,306
	Not informed	48	2,40	1,300
Communication	Informed about the DT	28	3,54	1,062
	Not informed	48	2,86	1,360

A statistically notable difference was identified in one factor. While no significant differences were found for the other factors ($p > 0.05$), a critical difference emerged in the communication factor ($p < 0.05$). In this analysis, since the p-values for Levene's test exceeded the conventional 0.05 threshold, the assumption of homogeneity of variances was considered satisfied.

Table 4.17 : Independent samples t-test results for the potential impact of DT on these factors.

Variables	Levene's Test for Equality of Variances		T-test for Equality of Means	
	F	Sig.	t	p
Labor	0,430	0,514	1,625	,108
Work Site	0,099	0,754	0,153	,879
Management System	3,924	0,051	1,252	,214
Industry Environment	0,571	0,452	0,075	,941
Design Related Issues	0,025	0,874	1,876	,065
Climate	0,061	0,805	-0,240	,811
Communication	3,406	0,069	2,241	,028*

* T-test result is significant at the 0.05 level.

Consequently, participants with knowledge of DT rated the communication factor significantly higher (i.e., 3.54) than those without (i.e., 2.86). This difference may be attributed to the fact that individuals with knowledge of DT technology recognize its potential benefits for communication related issues, thus perceiving a positive outcome if it were implemented. Moving on to questions related to DT perception, Table 4.18 provides the group statistics on DT benefits, while Table 4.19 presents the independent samples t-test results for these benefits.

Table 4.18 : Group statistics for the DT benefits.

Variables	Sample Group	N	Mean	Std. Deviation
Real Time Digital Representation	Informed about the DT	28	4,36	,826
	Not informed	48	4,06	1,060
Remote Monitoring	Informed about the DT	28	4,50	,577
	Not informed	48	4,21	,988
Resource Management	Informed about the DT	28	4,32	,772
	Not informed	48	4,10	,881
Safety Management	Informed about the DT	28	3,75	,927
	Not informed	48	3,58	1,007
Risk Management	Informed about the DT	28	4,11	,831
	Not informed	48	4,08	,820
Collaboration With Autonomous Robots	Informed about the DT	28	3,86	,970
	Not informed	48	4,02	1,061
Waste Reduction	Informed about the DT	28	3,39	1,065
	Not informed	48	3,85	,967
Predictive Decision Making	Informed about the DT	28	4,21	,875
	Not informed	48	4,04	1,030
Time And Cost Management	Informed about the DT	28	4,39	,628
	Not informed	48	4,25	,956
Communication And Collaboration	Informed about the DT	28	4,07	,899
	Not informed	48	3,79	,944

All variables show no statistically significant difference between the two groups, as their p-values exceed 0.05. These findings suggest that perceptions of DT benefits do not significantly differ based on knowledge about DT. Some participants may know about DT concepts but some of them lack practical experience in real world construction. This lack of direct exposure could lead to similar perceptions between informed and uninformed groups. However, since the mean values of DT benefits are high, the lack of direct exposure may not be considered a negative influence on perceptions. Instead, this might suggest that other factors, such as collective professional awareness and a positive attitude toward new technologies in the sector, may contribute to similar perceptions between informed and uninformed groups.

Table 4.19 : Independent samples t-test results for the benefits of DT.

Variables	Levene's Test for Equality of Variances		T-test for Equality of Means	
	F	Sig.	t	p
Real Time Digital Representation	0,882	0,351	1,263	,211
Remote Monitoring	5,104	0,027	1,424	,109
Resource Management	0,467	0,497	1,084	,282
Safety Management	0,960	0,330	0,716	,476
Risk Management	0,356	0,553	0,121	,904
Collaboration With Autonomous Robots	0,503	0,480	-0,669	,506
Waste Reduction	0,265	0,608	-1,931	,057
Predictive Decision Making	1,475	0,228	0,743	,460
Time And Cost Management	6,184	0,015	0,705	,435
Communication And Collaboration	0,636	0,428	1,267	,209

To assess whether there is a statistically significant difference in the perception of challenges in implementing DT between participants who are informed about DT and those who are not, an independent sample t-test was conducted. The group statistics for the challenges associated with DT implementation are displayed in Table 4.20 and the results are presented in Table 4.21. The findings indicate that for most challenges there is no statistically significant difference between the two groups ($p > 0.05$). However, three variables, data integration ($p = ,008$), high-fidelity model ($p = ,038$), and skill and training ($p = ,007$) show a statistically significant difference ($p < 0.05$). The question evaluates responses using a Likert scale, a lower mean indicates greater difficulty in the related challenges. Because for accurate assessment, the study's mean values have been reverse-coded in the t-test analysis of challenges in implementing DT. For data integration, the informed group reported a lower mean (i.e., 2.68) compared to the not informed group (3.46). Similarly, for high-fidelity models, the informed group had a lower mean (i.e., 2.79) than the not informed group (i.e., 3.42).

Table 4.20 : Group statistics for the challenges in implementing DT.

Variables	Sample Group	N	Mean	Std. Deviation
Adaptability	Informed about the DT	28	2,71	1,117
	Not informed	48	3,19	1,044
Data Integration	Informed about the DT	28	2,68	1,123
	Not informed	48	3,46	1,236
Data Management	Informed about the DT	28	2,82	1,156
	Not informed	48	3,40	1,283
High-Fidelity Model	Informed about the DT	28	2,79	1,315
	Not informed	48	3,42	1,217
Interoperability	Informed about the DT	28	2,82	1,020
	Not informed	48	3,27	1,180
Operation Cost	Informed about the DT	28	2,50	1,374
	Not informed	48	2,98	1,194
Cybersecurity and Privacy	Informed about the DT	28	2,57	1,200
	Not informed	48	2,94	1,262
Skill and Training	Informed about the DT	28	2,00	1,122
	Not informed	48	2,73	1,267
User Interface	Informed about the DT	28	2,54	1,071
	Not informed	48	2,96	1,220

Table 4.21 : Independent samples t-test results for the challenges in implementing DT.

Variables	Levene's Test for Equality of Variances		T-test for Equality of Means	
	F	Sig.	t	p
Adaptability	0,814	0,37	-1,856	,067
Data Integration	0,323	0,571	-2,739	,008*
Data Management	0,279	0,599	-1,95	,055
High-Fidelity Model	0,992	0,322	-2,116	,038*
Interoperability	0,718	0,400	-1,681	,097
Operation Cost	1,326	0,253	-1,596	,115
Cybersecurity and Privacy	0,022	0,883	-1,242	,218
Skill and Training	2,099	0,152	-2,521	,007*
User Interface	0,437	0,511	-1,522	,132

* T-test result is significant at the 0.05 level.

Lastly, for skill and training, the informed group reported a mean of 2.00, while the not informed group scored 2.73, indicating that individuals who are knowledgeable about DT perceive these aspects as greater challenges compared to those who are not. According to outputs we may state, informed participants can be more aware of the complexities involved in integrating DT within existing systems, achieving high resolution digital models and the need for specialized training about it. Their familiarity with DT may provide them with a deeper understanding of the technical, operational and skill related challenges involved in its implementation. Similarly, their awareness highlights a more critical perspective on the technological constraints of DT adoption. An independent sample t-test was performed to determine whether perceptions of key DT application areas in the construction phase differ between informed and uninformed participants. These are statistically overviewed in Table 4.22, while the results are detailed in Table 4.23. In this analysis, as the p-values from Levene's test were greater than the standard 0.05 threshold, the assumption of equal variances was considered satisfied.

Table 4.22 : Group statistics for the key applicaiton area of DT in the construction phase.

Variables	Sample Group	N	Mean	Std. Deviation
Workforce Oversight	Informed about the DT	28	3,79	,994
	Not informed	48	3,35	1,021
Material and Equipment Management	Informed about the DT	28	4,14	,755
	Not informed	48	3,92	1,007
Site Monitoring	Informed about the DT	28	4,32	,772
	Not informed	48	3,92	1,127
Optimization of Time and Cost	Informed about the DT	28	4,39	,685
	Not informed	48	4,04	1,091
Enhanced Decision Making Processes	Informed about the DT	28	4,36	,826
	Not informed	48	3,83	1,059
Integration with Emerging Technologies	Informed about the DT	28	4,00	,942
	Not informed	48	4,15	,850
Comprehensive Participation	Informed about the DT	28	3,89	1,031
	Not informed	48	3,81	1,024

Table 4.23 : Independent samples t-test results for the key applicaiton area of DT in the construction phase.

Variables	Levene's Test for Equality of Variances		T-test for Equality of Means	
	F	Sig.	t	p
Workforce Oversight	0,076	0,783	1,794	,077
Material and Equipment Management	2,631	0,109	1,03	,306
Site Monitoring	1,759	0,189	1,682	,097
Optimization of Time and Cost	4,538	0,036	1,534	,089
Enhanced Decision Making Processes	1,34	0,251	2,247	,028*
Integration with Emerging Technologies	0,138	0,711	-0,693	,491
Comprehensive Participation	0,375	0,542	0,329	,743

* T-test result is significant at the 0.05 level.

The findings indicate that except for one variable, the DT application areas show no statistically significant difference between the two groups ($p > 0.05$). At a 95% confidence interval, no significant differences were found between the two groups regarding most DT application areas. Nevertheless, enhanced decision making processes show a statistically significant difference (p = ,028). The mean scores indicate that participants who are informed about DT perceive this application area as more effective (i.e., 4.36) compared to those who are not informed (i.e., 3.83). This might mean that those who are already familiar with DT may be more aware of its capacity to enhance decision making effectiveness through the features of DT. Also they can be more familiar with how DT systems work, especially their capacity to combine huge amounts of project data into actionable insights. Lastly, an independent-samples t-test was conducted to determine whether there is a statistically significant difference in the perception of DT's effectiveness in improving productivity during the construction phase between participants who are informed about DT and those who are not. The group statistics for this assessment are presented in Table 4.24, while the results of the t-test are displayed in Table 4.25. Since the p-value of the independent samples t-test (p = 0,099) is greater than 0.05, there is no statistically significant difference between the two groups in their perception of DT's effectiveness in enhancing productivity during the construction phase.

Table 4.24 : Statistic for the assessment of DT's effectiveness.

Variables	Sample Group	N	Mean	Std. Deviation
The effectiveness of DT in improving productivity during construction phase	Informed about the DT	28	4,25	,585
	Not informed	48	4,00	,652

Although the mean score for participants informed about DT (i.e., 4.25) is slightly higher than that of those who are not informed (i.e., 4.00), the difference is not statistically significant. This may indicate that regardless of their past familiarity with the technology, both groups generally acknowledge DT's potential to increase construction productivity.

Table 4.25 : Independent samples t-test results for the assessment of DT's effectiveness.

Variables	Levene's Test for Equality of Variances		t-test for Equality of Means	
	F	Sig.	t	p
The effectiveness of DT in improving productivity during construction phase	0,389	0,535	1,672	,099

4.2.5 One-way ANOVA

In order to determine whether different levels of expertise in the sector lead to different opinions on DT system' perception , a One-Way ANOVA test was conducted. This statistical method allows for the comparison of means among three or more independent groups to assess whether there is a statistically significant difference. By applying this test, the study aims to identify potential variations in DT perception based on expertise levels, providing deeper insights into how different levels of professional experience influence views on the benefits, challenges and key application areas of DT technology in the construction industry. The initial grouping for the ANOVA tests was determined based on the respondents' level of expertise in the sector. Participants were classified into three distinct categories: those with less than two years of experience, those with two to five years of experience, and those with more than five years of experience. Accordingly, the 76 participants were distributed as follows: 14 with less than 2 years of experience, 44 with 2 to 5 years experience, and 18 with more than 5 years experience.

The results for the benefits of DT are presented in Table 4.26.

Table 4.26 : One-way ANOVA results for the benefits of DT.

Variables	Group	N	Mean	Std. Deviation	ANOVA-p value
Real Time Digital Representation	< 2 years	14	4,14	1,167	,939
	2-5 years	44	4,20	,851	
	> 5 years	18	4,11	1,183	
Remote Monitoring	< 2 years	14	4,00	1,038	,325
	2-5 years	44	4,39	,813	
	> 5 years	18	4,39	,850	
Resource Management	< 2 years	14	4,14	,864	,968
	2-5 years	44	4,20	,878	
	> 5 years	18	4,17	,786	
Safety Management	< 2 years	14	3,43	,938	,189
	2-5 years	44	3,57	,998	
	> 5 years	18	4,00	,907	
Risk Management	< 2 years	14	4,07	,616	,991
	2-5 years	44	4,09	,910	
	> 5 years	18	4,11	,758	
Collaboration with Autonomous Robots	< 2 years	14	3,93	1,328	,986
	2-5 years	44	3,98	,902	
	> 5 years	18	3,94	1,110	
Waste Reduction	< 2 years	14	4,07	,829	,244
	2-5 years	44	3,55	1,109	
	> 5 years	18	3,72	,895	
Predictive Decision Making	< 2 years	14	4,00	1,038	,903
	2-5 years	44	4,14	,930	
	> 5 years	18	4,11	1,079	
Time And Cost Management	< 2 years	14	4,43	,646	,794
	2-5 years	44	4,30	,930	
	> 5 years	18	4,22	,808	
Communication And Collaboration	< 2 years	14	4,14	,770	,522
	2-5 years	44	3,86	,955	
	> 5 years	18	3,78	1,003	

In the evaluation of the questionnaire, which assessed a total of ten benefits, no statistically significant differences were found between the groups, as all the p-values were greater than 0.05. We can conclude that opinions of the benefits of DT technology do not differ statistically significantly depending on their level of experience. The similarity in view may be explained by the fact that people of all experience levels are generally aware of DT's benefits. Less experienced professionals may recognize the potential benefits of DT due to educational resources and conferences, while more experienced professionals, through their practical knowledge, may be more aware of the need for the benefits that DT technology provides. Overall, the findings show that opinions toward the positive aspects of DT are not significantly influenced by their level of expertise. For a further analysis a larger sample size might provide clearer insights into whether experience influences perceptions of these challenges. Table 4.27 displays One-way ANOVA results for the challenges in implementing DT. In the ANOVA results, the mean values are based on a Likert scale, higher mean scores (closer to 5) indicate less difficulty, while lower scores (closer to 1) indicate greater difficulty.

Table 4.27 : One-way ANOVA results for the challenges in implementing DT.

Variables	Group	N	Mean	Std. Deviation	ANOVA-p value
Adaptability	< 2 years	14	2,86	1,167	,052*
	2-5 years	44	2,84	1,033	
	> 5 years	18	3,56	1,042	
Data Integration	< 2 years	14	3,07	1,492	,330
	2-5 years	44	3,05	1,160	
	> 5 years	18	3,56	1,247	
Data Management	< 2 years	14	3,14	1,460	,354
	2-5 years	44	3,05	1,257	
	> 5 years	18	3,56	1,097	
High-Fidelity Model	< 2 years	14	2,93	1,592	,608
	2-5 years	44	3,18	1,187	
	> 5 years	18	3,39	1,290	
Interoperability	< 2 years	14	2,93	1,269	,240
	2-5 years	44	3,00	1,121	
	> 5 years	18	3,50	1,043	

* ANOVA result is significant at the 0.05 level.

Table 4.27 (continued): One-way ANOVA results for the challenges in implementing DT.

Variables	Group	N	Mean	Std. Deviation	ANOVA-p value
Operation Cost	< 2 years	14	2,64	1,216	,281
	2-5 years	44	2,68	1,360	
	> 5 years	18	3,22	1,060	
Cybersecurity and Privacy	< 2 years	14	2,36	1,008	,212
	2-5 years	44	3,00	1,201	
	> 5 years	18	2,67	1,455	
Skill and Training	< 2 years	14	2,29	,994	,463
	2-5 years	44	2,39	1,298	
	> 5 years	18	2,78	1,353	
User Interface	< 2 years	14	2,57	1,284	,716
	2-5 years	44	2,84	1,140	
	> 5 years	18	2,89	1,231	

* ANOVA result is significant at the 0.05 level.

In the analysis, nine challenges were examined, and no significant differences in perceptions were observed among the groups except for one variable, adaptability, as their p-values were greater than 0.05. The variable that showed a borderline significance was adaptability performance, with a p-value of 0.052. Since this value is very close to the 0.05 significance threshold, further analysis may provide more insight into potential differences. As the next step, post-hoc analyses were conducted to determine which groups were responsible for this difference. To determine the appropriate post-hoc test, Levene's test for homogeneity of variances performed on the adaptability performance variable and the results are presented in Table 4.28.

Table 4.28 : Levene Statistic results for homogeneity of variances for adaptability.

Variable	Levene Statistic	Sig.
Adaptability	0,029	,972

The p-value of Levene's test was ,972. Since this value is greater than 0.05, it indicates that the data is homogeneously distributed. Therefore, Gabriel’s Test and Tukey’s Test were applied to analyze differences in adaptability performance. The test results shown in Table 4.29. In the post-hoc analysis, a statistically significant difference was identified between the perceptions of individuals with 2–5 years of experience and those with more than 5 years of experience. This difference was confirmed with a significance value of 0.048 in Tukey's test and 0.047 in Gabriel's test. The findings of both tests were equal as given in 4.24 with only minor numerical differences. The mean difference of 0.715 between the more than 5 years of experience and 2–5 years of experience groups indicates that participants with more than 5 years of experience rated the adaptability variable higher than the other group. Since the mean difference is positive (i.e., 0.715) and statistically significant ($p = 0.048$ in Tukey and $p = 0.047$ in Gabriel, both < 0.05) it suggests that respondents with more than 5 years of experience perceive adaptability challenge more positively than those with 2–5 years of experience. This might signify that more experienced professionals might have a better understanding of adaptability challenges in DT applications and may perceive this issue as easily manageable. In contrast, those with moderate experience, 2–5 years, may have greater concerns regarding adaptability, which may stem from their tendency to perceive it as a fundamental issue rather than a manageable challenge. Additionally, for most variables the sample size for each experience group may not be large enough to detect statistically significant differences.

Table 4.29 : Tukey's and Gabriel's post-hoc tests results for adaptability.

Post-Hoc Test	Group(I)	Group (J)	Mean Difference (I-J)	Std. Error	Sig.
Tukey HSD	< 2 years	2-5 years	,016	0,325	,999
		> 5 years	-,698	0,378	,161
	2-5 years	< 2 years	-,016	0,325	,999
		> 5 years	-,715**	0,297	,048**
	> 5 years	< 2 years	,698	0,378	,161
		2-5 years	,715**	0,297	,048**
Gabriel	< 2 years	2-5 years	,016	0,325	1,000
		> 5 years	-,698	0,378	,189
	2-5 years	< 2 years	-,016	0,325	1,000
		> 5 years	-,715**	0,297	,047**
	> 5 years	< 2 years	,698	0,378	,189
		2-5 years	,715**	0,297	,047**

** The mean difference is highly significant at the 0.05 level, $p < 0.05$.

Table 4.30 presents the One-Way ANOVA results for the key applications of DT during the construction phase. In the analysis, seven major application areas were examined, and no significant differences in perceptions were found among the groups for six of these variables, as their p-values were greater than 0.05.

Table 4.30 : One-way ANOVA results for the key applications of DT during the construction phase.

Variables	Group	N	Mean	Std. Deviation	ANOVA-p value
Workforce Oversight	< 2 years	14	3,14	1,099	,296
	2-5 years	44	3,64	,892	
	> 5 years	18	3,50	1,249	
Material&Equipment Management	< 2 years	14	4,29	,726	,308
	2-5 years	44	4,00	,889	
	> 5 years	18	3,78	1,114	
Site Monitoring	< 2 years	14	3,93	1,207	,770
	2-5 years	44	4,14	,878	
	> 5 years	18	4,00	1,237	
Optimization of Time and Cost	< 2 years	14	4,29	,914	,674
	2-5 years	44	4,20	,904	
	> 5 years	18	4,00	1,188	
Enhanced Decision Making Processes	< 2 years	14	4,14	,663	,768
	2-5 years	44	4,05	1,011	
	> 5 years	18	3,89	1,231	
Integration with Emerging Technologies	< 2 years	14	4,29	,726	,049*
	2-5 years	44	3,89	,920	
	> 5 years	18	4,44	,784	
Comprehensive Participation	< 2 years	14	3,79	1,122	,444
	2-5 years	44	3,75	,991	
	> 5 years	18	4,11	1,023	

* ANOVA result is significant at the 0.05 level.

However, a statistically significant difference was observed in integration with emerging technologies, with a p-value of 0.049. To further investigate this difference, post-hoc analyses were conducted to identify which groups contributed to the variation. To select the appropriate post-hoc test, Levene’s test for homogeneity of variances was applied to the integration with emerging technologies variable, and the results are displayed in Table 4.31. The p-value of Levene’s test was 0.194, indicating that the data was homogeneously distributed (p > 0.05). Therefore Tukey's and Gabriel's tests were employed to examine how perceptions varied among groups.

Table 4.31 : Levene Statistic results for homogeneity of variances for integration with emerging technologies.

Variable	Levene Statistic	Sig.
Integration with Emerging Technologies	1,675	,194

As shown in Table 4.32, with a few minor number variations, the results of the two tests were the same. The post-hoc results revealed a borderline significant difference between participants with 2–5 years of experience and those with more than 5 years of experience, with p-values of 0.059 in Tukey’s test and 0.058 in Gabriel’s test. Although these values are slightly above the 0.05 significance threshold, these numbers indicate a possible trend where respondents with more than 5 years of experience rated the application of integration with emerging technologies more positively than those with 2–5 years of experience as indicated by the mean difference of 0.558.

Table 4.32 : Tukey’s and Gabriel’s post-hoc tests results for integration with emerging technologies.

Post-Hoc Test	Group(I)	Group (J)	Mean Difference (I-J)	Std. Error	Sig.
Tukey HSD	< 2 years	2-5 years	,399	0,263	,289
		> 5 years	-,159	0,306	,862
	2-5 years	< 2 years	-,399	0,263	,289
		> 5 years	-,558*	0,240	,059*
	> 5 years	< 2 years	,159	0,306	,862
		2-5 years	,558*	0,240	,059*
Gabriel	< 2 years	2-5 years	,399	0,263	,315
		> 5 years	-,159	0,306	,937
	2-5 years	< 2 years	-,399	0,263	,315
		> 5 years	-,558*	0,240	,058*
	> 5 years	< 2 years	,159	0,306	,937
		2-5 years	,558*	0,240	,058*

* The mean difference is significant at the 0.05 level, p < 0.05.

Nevertheless, since the results do not have a p-value below 0.05, the differences between responses cannot be considered statistically significant. There is a possibility that it may reveal a meaningful pattern. Nonetheless, it can be clearly stated that no statistically significant differences exist in other major application areas based on years of experience. This may be due to the fact that these key areas are widely recognized and reflect a shared understanding across all participants. Neither increased experience in the sector nor recent education and information about technologies appears to influence their perceived importance, as they are accepted within the industry. Overall, if the study had included a larger sample size, this uncertainty in the results might not have occurred, as the ANOVA p-value, despite being close to 0.05 ($p = 0.058$), does not indicate a statistically significant difference between groups.

5. CONCLUSION

Productivity is a major concern in the construction industry, as the sector consistently faces low performance levels. A common explanation for the efficiency gap is the construction sector's resistance to adopting new technologies and its continued reliance on traditional methods (Menegon and Filho, 2022; Laszig et al., 2020). This reliance on conventional practices limits the industry's ability to benefit from innovations that could optimize operations, improve coordination and reduce errors. While advancements usually enhance productivity, the industry's slow adoption of innovative technologies might be a contributing factor to its slower development. Nevertheless, technological developments continue to play a crucial role in improving productivity within the construction sector (Alzubi et al., 2023; Akanmu et al., 2021). Recent studies emphasize the growing role of DT technology in transforming the construction industry through its integration with emerging technologies such as AI, IoT, DL/ML, immersive technologies, robotics and blockchain. Among these innovations, DT technology is a noteworthy concept to provide a centralized platform for real time insights, performance tracking, simulation, forecasting and analysis. DT notably brings together advanced technologies, employing them both as enabling technologies and as critical contributors to the creation of DT. Therefore, the DT concept is gaining popularity for its potential to enhance efficiency. Moreover it is also recognized for its ability to provide current time, dynamic representations of physical assets throughout the project lifecycle. Its capacity to combine data from multiple sources contributes significantly to its growing attraction. The integration of data from various sources such as BIM models and IoT sensors enables a comprehensive understanding of project status and performance. Researchers highlight its potential to improve lifecycle management, efficiency, sustainability and predictive maintenance. The need of DT technology becomes especially clear during the construction stage, when rework, uncertainty and inefficiencies are most common. Despite the potential, the literature also notes barriers to DT system adoption such as economic, technical and organizational obstacles. Although still in the early phases of integration in the sector, the rising curiosity in DT underlines its capacity for enhancing industry performance. In general, the literature demonstrates that DT is regarded as a key innovation and plays an important role in the context of smart construction.

The objectives of this thesis were as follows: (1) to explore the role of DT throughout the building life cycle in the construction sector; (2) to identify its benefits, challenges and key application areas in the construction stage; (3) to determine the factors affecting productivity during the construction phase; and (4) to compare these factors with the DT system's identified capabilities to assess its potential in overcoming productivity challenges. In this context, this study aims to investigate how DT technology can address productivity challenges in the construction phase. Aligned with the objectives, a comprehensive literature review was conducted to identify the key factors influencing productivity during the construction stage, and to analyze the benefits, challenges and major application areas of DT in this phase. In this study, the methodology involved a survey to examine the potential impact of DT on construction productivity factors and to assess how DT is perceived by industry professionals. The survey aimed to explore views of respondents on the advantages, obstacles in implementing the technology and the main application areas of DT. Also it is gathering opinions on how these features may influence productivity related factors during the construction phase. To support the research objective, the questionnaire was developed based on a literature review that identified productivity factors and outlined DT technology in terms of its opportunities, implementation challenges and applications. These elements were then incorporated into the survey design. Following its distribution to professionals across the industry, the survey received 76 responses. All responses were considered valid and included in the analysis. Then, the results were examined using the SPSS v.29 software to evaluate the collected data and obtain meaningful statistical insights.

In accordance with the research objectives, the study first examined the role of DT throughout the building life cycle in the construction sector. To achieve this goal, the study conducted a literature review and a bibliometric analysis. The analysis reveals that the concept of DT has gained increasing importance in the building life cycle. According to an examination of articles, an essential increase in academic studies related to DT has been observed in recent years. Moreover, although traditional themes remain significant, it can be revealed that emerging technologies such as AI and the IoT are rapidly gaining adoption in the sector. Also the research trends are increasingly shifting toward more specialized areas. For instance, it has been identified that over time, the focus of keywords has shifted from broader topics such as BIM, Industry 4.0 and construction to more specialized and technical subjects like predictive maintenance, big data and AI. This may indicate that technological advancements related to DT have the potential to rapidly introduce new concepts and applications in the construction sector. Keyword co-occurrence maps have demonstrated that DT technology in construction related studies is closely associated with disciplines such as computer science, AI, IoT and machine learning systems. Moreover, the analyzed keywords might play different roles across various stages of the construction life cycle. For instance, risk management and BIM are more commonly emphasized in the design phase, whereas IoT, smart contracts, optimization and simulation are mainly linked to the construction phase. Advancements such as cyber-physical systems and facility management are likely to play a significant role during the operation and maintenance stages, while concepts like circular economy and waste minimization are expected to be more relevant in the end-of-life stage of a building’s life cycle. In addition, enhancements in information technologies may directly influence the development of DT technology in the construction sector, as the literature frequently highlights a close connection between the improvement of DT in the building industry and digital infrastructure. Also in the literature researchers emphasize that DT technology can significantly enhance construction processes by enabling more effective management of resources, budgets and schedules. The adoption of construction DT systems (CDT) is regarded as a transformative development for the industry, offering advantages such as cost reduction, improved environmental responsibility and advanced lifecycle management (Boje et al., 2020). It also supports decision making, progress tracking and site coordination (Piras et al., 2024; Jiang et al., 2021). DT begins to take form during the construction phase and facilitates the monitoring of progress, management of site operations and tracking of safety, environmental and cost related parameters (Chen et al., 2024). Additionally, DT supports predictive maintenance, optimizes resource use and improves overall building performance. In summary, DT contributes to more efficient construction management through real time monitoring, data driven planning and enhanced coordination (Teisserenc and Sepasgozar, 2021). Furthermore, the construction phase plays a vital role in the building life cycle, since it is the stage where design concepts are transformed into physical structures, and where time, cost, quality and safety performance directly influence project outcomes (Opoku et al., 2021; Yang et al., 2024). Therefore, the construction phase of the building life cycle was selected as the focus of the research.

As the second objective, the study identifies the benefits, challenges and key application areas of DT in the construction stage. DT technology offers various advantages that can be effectively utilized in the construction sector (Ellul et al., 2024; Elfarri et al., 2022; Hosamo et al., 2022). The literature highlights several of these benefits. For instance, its real time digital representation enables accurate and current visualization of construction progress and site conditions (Deria et al., 2022). Remote monitoring allows stakeholders to manage activities from off site locations, which improves oversight (Jiang et al., 2021). Resource management is enhanced through more efficient allocation and tracking of labor, materials and equipment (Hu et al., 2022). DT also strengthens safety management by identifying potential hazards early and simulating risk scenarios, thereby helping to prevent accidents (Wu et al., 2022). Its predictive capabilities support risk management by allowing professionals to anticipate and address issues before they become more serious (Salem and Dragomir, 2023). Another notable advantage is its ability to collaborate with autonomous robots, increasing productivity by automating repetitive or hazardous tasks (Li et al., 2021). Additionally, DT contributes to waste reduction by optimizing material usage and minimizing errors (Debrah et al., 2022). Furthermore its use of data driven algorithms supports predictive decision making and improves forecasting accuracy (Turner et al., 2021). Time and cost management benefit from its ability to enhance scheduling and more effective resource utilization (Bakhshi et al., 2024). Finally, communication and collaboration are improved through a centralized platform that enables real time information sharing among project stakeholders (Zhang et al., 2024). Together, these features demonstrate the growing potential of DT concept to enhance efficiency in construction projects. While DT technology offers numerous advantages for the construction industry, the literature also highlights several challenges that may restrict its effective adoption. Despite its potential, certain areas present significant barriers to integration (Sun et al., 2022).

One of these challenges is the need for adaptability, data integration and data management, all of which require reliable systems capable of handling large volumes of complex information (Opoku et al., 2024; Lu et al., 2020a; Riaz et al., 2015). Also developing high-fidelity models is another challenge, since it is necessary for generating accurate simulations (Bilberg and Malik, 2019). In addition, interoperability between different digital tools and platforms is a critical issue (Lu et al., 2020b). Moreover, operational costs associated with DT implementation can be high, particularly for smaller firms (Moshood et al., 2024). Furthermore, concerns related to cybersecurity and data privacy present risks that must be carefully addressed (Ghosh et al., 2020). The need for specialized skills and training leads to another challenge, as many professionals may lack the technical expertise required to operate DT systems effectively (Bilberg and Malik, 2019). Usability challenges, such as the complexity of user interfaces, also affect how well stakeholders interact with the technology (Boje et al., 2020). Despite these challenges, the literature emphasizes a variety of applications for DT technology in both architecture and construction. When focusing specifically on its applications during the construction phase, key application areas are identified in the literature. These include workforce oversight, allowing better management and coordination of labor on site (Boje et al., 2023); material and equipment management, which supports efficient tracking and allocation of resources (Jiang et al., 2021); site monitoring, which ensures current time monitoring of progress and performance (Akanmu and Anumba, 2015). Additionally, DT contributes to the optimization of time and cost (Salih and El-adaway, 2024), enhances the decision making process through insights gained from data (Yang et al., 2024) and facilitates integration with emerging technologies such as IoT and AI (Moshood et al., 2024). Another important aspect is comprehensive participation, where DT enables improved collaboration among various stakeholders throughout the construction process (Arowoiya et al., 2023). These applications underline the growing importance of DT in transforming traditional construction practices into more intelligent and efficient systems.

Afterwards, to evaluate the findings from the literature in light of industry professionals' perspectives, descriptive statistics were applied to the survey results to illustrate data distribution and identify fundamental patterns. Survey results indicate that according to participants the most valued benefits of DT technology are remote monitoring, time and cost management, and resource management. These are followed by real time digital representation, predictive decision making and risk management. Benefits such as safety management and waste reduction received relatively lower scores but are still recognized as meaningful contributions of DT in the construction phase. Even the lowest rated opportunities received relatively high mean scores. This may reflect appreciation of participants for their usefulness. Furthermore, according to participants the main challenges in implementing DT technology are skill and training, user interface, cybersecurity and privacy, and operation cost. These are followed by adaptability, interoperability, data integration, data management and lastly high-fidelity modeling. These findings can suggest that participants are more concerned with human, privacy and usability obstacles than with technical issues. As reported by industry experts, the major application areas of the DT system during the construction phase include the optimization of time and cost, integration with emerging technologies, site monitoring, enhanced decision making processes, material and equipment management, comprehensive participation and workforce oversight, respectively. Moreover, participants expressed a strong agreement on the effectiveness of DT in enhancing productivity during the construction phase, as reflected in the high mean score. After the descriptive statistics, the reliability of the survey scales was assessed using Cronbach’s Alpha, which revealed acceptable levels of internal consistency across all scales. In the next step, normality tests were applied to the data, and it was normally distributed. The correlation analysis revealed that a majority of the variables showed statistically significant relationships. When correlations above 0.60 were considered highly significant at the 0.01 level, in the benefits of the DT group, significant correlations were found between risk management and both real time digital representation and resource management. In addition, a correlation was also observed between time and cost management, and resource management. In contrast, the challenges in implementing DT category revealed a greater number of highly significant correlations. Among these, the strongest three were observed between data integration and both data management and high-fidelity model, as well as between data management and high-fidelity model. Finally, in the key applications of DT during the construction phase group, strong statistical correlations were observed between material and equipment management and both site monitoring and optimization of time and cost. Additionally, a similar strong relationship was observed between site monitoring and time and cost optimization. Following the correlation analysis between the scales, further analysis was conducted to examine whether there were significant differences in participants’ perceptions by categorizing them into relevant groups. For the independent samples t-test, the responses of DT-informed and non-informed participants were compared. In the examination of the responses related to the benefits of the DT category, no statistically significant difference was detected between DT-informed and non-informed participants. As the mean scores were high for both groups, this result may indicate that participants regardless of their awareness of DT, have a strong understanding of its benefits, which could explain the lack of notable difference between the groups. In the challenges in implementing the DT category, more statistically significant differences were discovered between the two groups compared to the other categories. These were found in the variables of data integration, high-fidelity model and skill and training. The DT-informed group reported lower mean scores for data integration, high-fidelity model and skill and training. This may demonstrate that respondents with DT knowledge perceive greater challenges in these areas compared to the non-informed group. Within the key application areas of DT in the construction phase category, a statistically significant difference was found only in the enhanced decision making processes variable. Participants with prior knowledge of DT rated the application area more highly than those without such knowledge. This could show that participants familiar with DT have greater insight into how it supports decision making, leading them to value this application area more highly. Lastly, in the assessment of DT's general effectiveness in improving productivity during the construction phase, similarly no statistically significant difference was found between the two groups. Since the mean scores were high in both groups, it might reveal that participants shared a common understanding of DT’s overall effectiveness, which explains the absence of a significant difference. An additional analysis was conducted to examine whether experience levels affected views of professionals and attitudes toward DT technology. Thus, for the ANOVA analysis, the respondents were divided into three groups based on their level of expertise: less than 2 years of experience, 2–5 years, and more than 5 years. Their responses were then compared to determine whether any statistically significant differences existed between the groups. Responses were examined with a focus on three categories: the benefits of DT, the challenges in implementing DT, and the key application areas of DT during the construction phase. First, in the analysis of the benefits of DT, no statistically significant differences were found among the three experience groups. All groups reported high mean scores for the related variables, indicating that DT's benefits were assessed generally highly positive. In the next step of the analysis, focusing on the challenges in implementing DT, a significant difference emerged only in the adaptability variable. Participants with more than 5 years of experience reported a higher mean score compared to those with 2–5 years of experience. This could suggest that more experienced professionals hold a more positive view regarding adaptability performance in the context of DT implementation. In terms of the final category, key application areas of DT during the construction phase, only one statistically significant difference was identified. Participants with more than 5 years of experience gave the variable integration with emerging technologies a higher mean score than those with 2–5 years of experience. This finding may imply that more experienced professionals place greater importance on DT's potential to integrate with emerging technologies. The limited variation in responses and the absence of major differences between the groups, along with consistently high mean scores, may reflect a shared perception and a generally optimistic attitude toward DT technology among the participants.

The third objective of the study is to identify the factors that influence productivity in the construction phase. In the literature, there are several factors that influence productivity during the construction phase. However, the main factors influencing productivity were revealed to include labor, work site, management systems, industry environment, design related issues, climate, and communication (Alzubi et al., 2023; Mehta et al., 2022; Hasan et al., 2018; Heravi and Eslamdoost, 2015). According to the research, each productivity factor in the construction sector consists of subcategory elements. The labor factor includes subcategories such as skill, training, and motivation. The worksite factor includes elements like site layout and site location. For management systems, the significant variables are cost management, quality management, time management, material and equipment management, decision making ability, and organizational methods. The design related issues factor involves financial uncertainties and regulatory changes. Within the industry environment category, constructability and inaccuracies in drawings are noted as significant subcomponents. The climate factor is represented by adverse weather conditions, while the communication factor includes challenges such as misunderstandings and communication barriers. These subcategory elements provide a more detailed understanding of how each factor can influence productivity in construction projects. To analyze respondents' answers to the relevant survey questions, descriptive statistics were applied to examine the distribution of responses. According to the results of the survey, the impact of seven key factors on productivity during the construction phase was ranked based on their mean scores. The findings reveal that labor was perceived as the most influential factor. This was followed by the management system and design related issues. Then, the factors were ranked as follows: work site conditions, industry environment, communication, and climate. In terms of occurrence frequency, the same factors were ranked based on their mean scores as follows: Labor, management system, design-related issues, industry environment, communication, work site and climate. According to professionals; labor, management systems and design related issues were not only ranked as the top three factors affecting productivity but were also the most frequently reported problem areas in construction projects. Following the descriptive analysis, the reliability of the survey scales was evaluated using Cronbach’s Alpha, which indicated acceptable internal consistency across all measurement items. A normal distribution of the data was observed. The correlation analysis demonstrated that most variables were significantly related at the 0.01 level. The analysis, considering correlations above 0.60 as highly significant, showed strong relations between the management system and both labor and design factors, also between work site conditions and design-related issues.

In the occurrence frequency of the factors group, a strong significant correlation was found only between climate and industry environment. After examining the correlations between the scales, additional analyses were performed to determine whether perceptions of industry experts differed across defined groups. An independent samples t-test was used to compare the responses of participants with prior knowledge of DT and those without. No statistically significant difference was observed between the two groups in their responses regarding factors impacting productivity during the construction phase and the occurrence frequency of these factors. This finding was expected, since awareness of DT technology may not affect participants' views in this area.

The fourth objective of the study is to compare these factors with the identified capabilities of the DT system in order to evaluate its potential for addressing productivity challenges. Descriptive analysis was conducted to interpret the response patterns to relevant questions in the survey. When participants were asked how the productivity related factors might be affected if DT technology were implemented in the construction phase, the ranking based on mean scores was as follows: Design related issues, management system , work site, communication, labor, industry environment and climate. According to industry experts, although labor is regarded as the most critical and frequently observed factor affecting productivity during the construction stage, the use of DT technology is believed to have its greatest impact on design related issues and management systems. Moreover, since design related issues and management systems identified as the two factors most positively impacted by DT also rank among the top three productivity factors in both impact and frequency in construction phase, this supports a positive perception that DT can effectively enhance productivity in construction. Furthermore, a comparative analysis of participants' responses concerning the factors influencing productivity and the key application areas of DT enables a more informed evaluation. Although labor was identified as the most influential factor affecting productivity during the construction phase, its related application area, workforce oversight, was ranked last among DT system's key application areas. This may suggest that participants do not perceive DT as particularly beneficial in addressing labor related issues. In contrast, management systems, previously identified by respondents as the second most problematic area, are closely linked to the top ranked application area of time and cost optimization, supporting the view that DT may significantly enhance efficiency in the management area. Similarly, another management related application area, enhanced decision making processes, also received a high mean score, further strengthening this view. Additionally, design related issues, ranked as the third most important factor affecting productivity, can be linked to the second ranked DT application area, integration with emerging technologies. Respondents may have thought that technologies such as AR, VR, AI, and IoT can help address design problems by enabling real time comparisons between architectural drawings, models and on-site implementation in the construction phase. Among the application areas, site monitoring and material & equipment management can be associated with the work site factor, ranked fourth in terms of its impact on efficiency. This indicates that DT may offer notable benefits in managing on site activities. Since industry environment and climate are external factors, a high level of impact from DT in these areas was not expected, which is also reflected in the results. Moreover the low ranking of communication as a productivity factor aligns with the similarly low position of comprehensive participation among DT applications. This may suggest that professionals do not perceive stakeholder communication as a major challenge during the construction phase, and therefore consider this application area less essential compared to others.

In the next evaluation, Cronbach’s Alpha confirmed acceptable reliability across the survey scales measuring how the implementation of DT in the construction phase could impact productivity related factors. The data showed a normal distribution. For the correlation analysis, it revealed significant relationships among most variables. Highly strong correlations were observed between climate and both work site and industry environment. Following the correlation analysis, a t-test was conducted to compare perceptions between DT-informed and non-informed participants. An analysis of the group responses related to the category revealed that a statistically significant difference was found only for the communication factor. The mean score of the DT-informed group was higher than the non-informed group. This finding might suggest that participants who are knowledgeable about DT are more likely to understand the role of DT in enhancing communication during the construction phase.

This study has a few limitations. First, although the sample size was sufficient for analysis, it may not fully reflect the diversity of the construction industry. Also the findings are limited to a local context. Another limitation is the relatively small number of participants who had direct experience with DT technology. This restricts the ability to assess real performance results based on practical application.

For future research, this examination can be extended to other phases of a construction project's lifecycle such as the design, operation, and end of life stages, since the current study focuses on the construction phase. Moreover, alongside survey based techniques, methodological approaches such as case studies or interviews with professionals from companies actively using DT may provide deeper insights and more detailed evaluations.

The research examines the impact of DT technology on productivity during the construction phase. Distinct from previous research, it first identifies the key factors that influence productivity in the construction stage and then investigates whether DT can have a direct effect on these factors. Insights were collected through a survey of industry professionals to assess DT's perceived potential. The results reveal that professionals generally maintain a positive and curious attitude toward DT, recognizing its potential to address existing problems and enhance construction efficiency.

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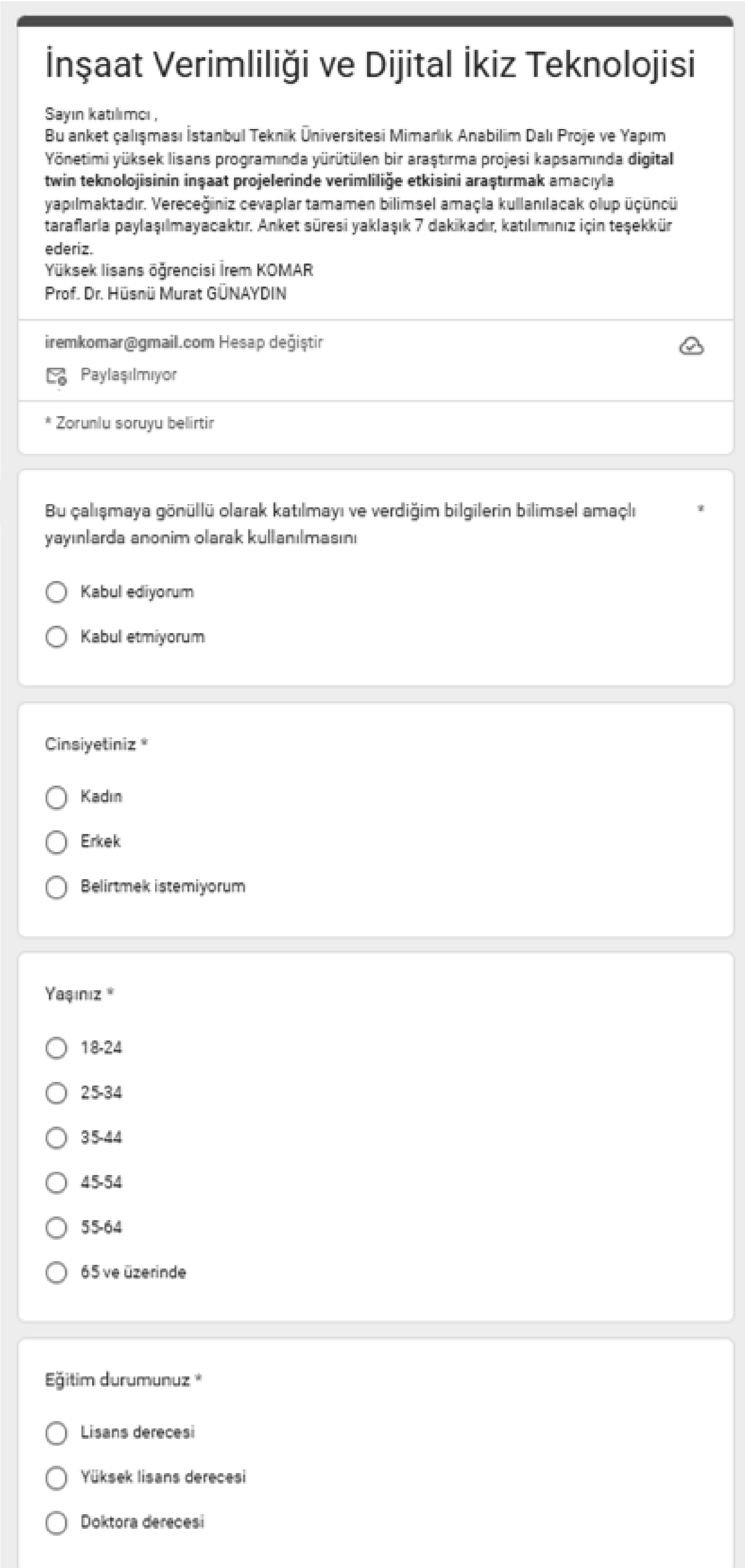
APPENDICES

APPENDIX A: Survey questions

APPENDIX A



İnşaat Verimliliği ve Dijital İkiz Teknolojisi

Sayın katılımcı ,
Bu anket çalışması İstanbul Teknik Üniversitesi Mimarlık Anabilim Dalı Proje ve Yapım Yönetimi yüksek lisans programında yürütülen bir araştırma projesi kapsamında **digital twin teknolojisinin inşaat projelerinde verimliliğe etkisini araştırmak** amacıyla yapılmaktadır. Vereceğiniz cevaplar tamamen bilimsel amaçla kullanılacak olup üçüncü taraflarla paylaşılmayacaktır. Anket süresi yaklaşık 7 dakikadır, katılımınız için teşekkür ederiz.
Yüksek lisans öğrencisi İrem KOMAR
Prof. Dr. Hüsnü Murat GÜNAYDIN

iremkomar@gmail.com Hesap değiştir
Paylaşılmıyor

* Zorunlu soruyu belirtir

Bu çalışmaya gönüllü olarak katılmayı ve verdiğim bilgilerin bilimsel amaçlı yayınlarda anonim olarak kullanılmasını *

- Kabul ediyorum
- Kabul etmiyorum

Cinsiyetiniz *

- Kadın
- Erkek
- Belirtmek istemiyorum

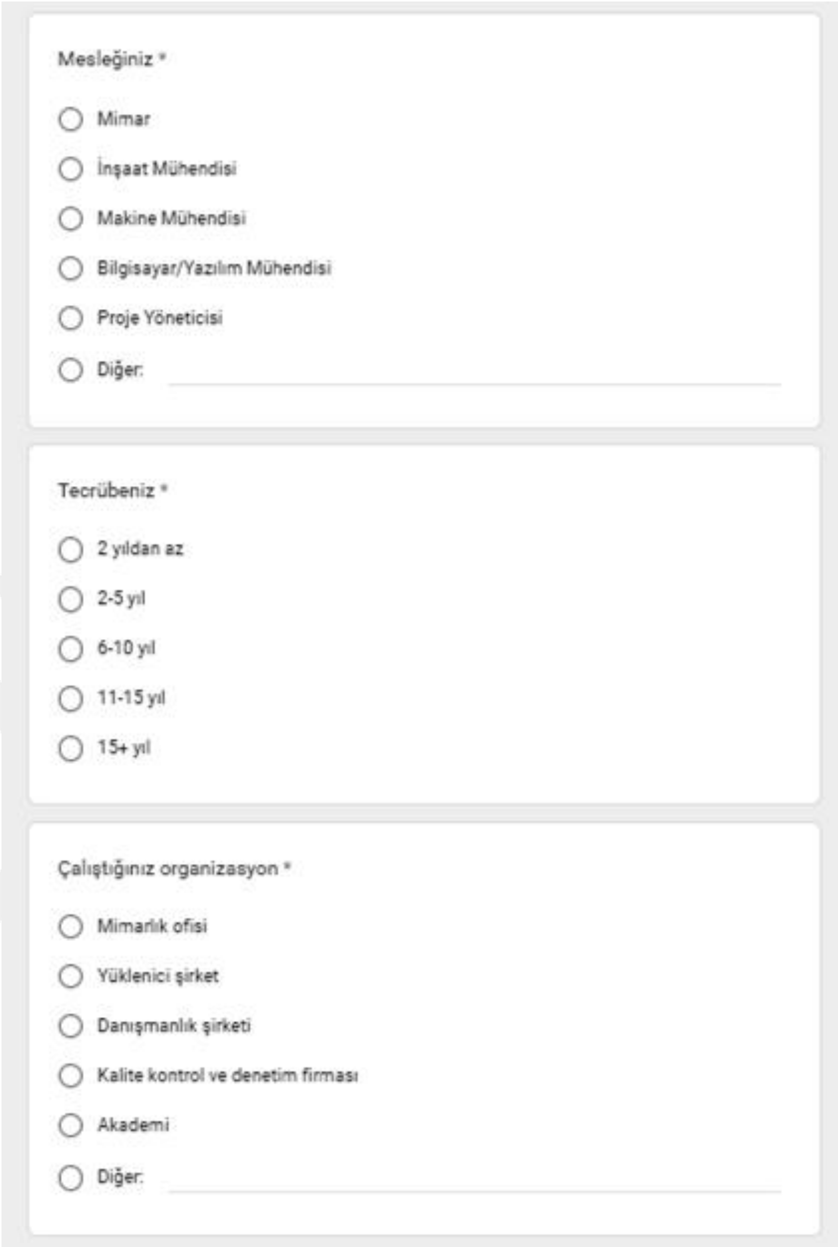
Yaşınız *

- 18-24
- 25-34
- 35-44
- 45-54
- 55-64
- 65 ve üzerinde

Eğitim durumunuz *

- Lisans derecesi
- Yüksek lisans derecesi
- Doktora derecesi

Figure A.1 : Questionnaire personal information part.


Mesleğiniz *

- Mimar
- İnşaat Mühendisi
- Makine Mühendisi
- Bilgisayar/Yazılım Mühendisi
- Proje Yöneticisi
- Diğer:

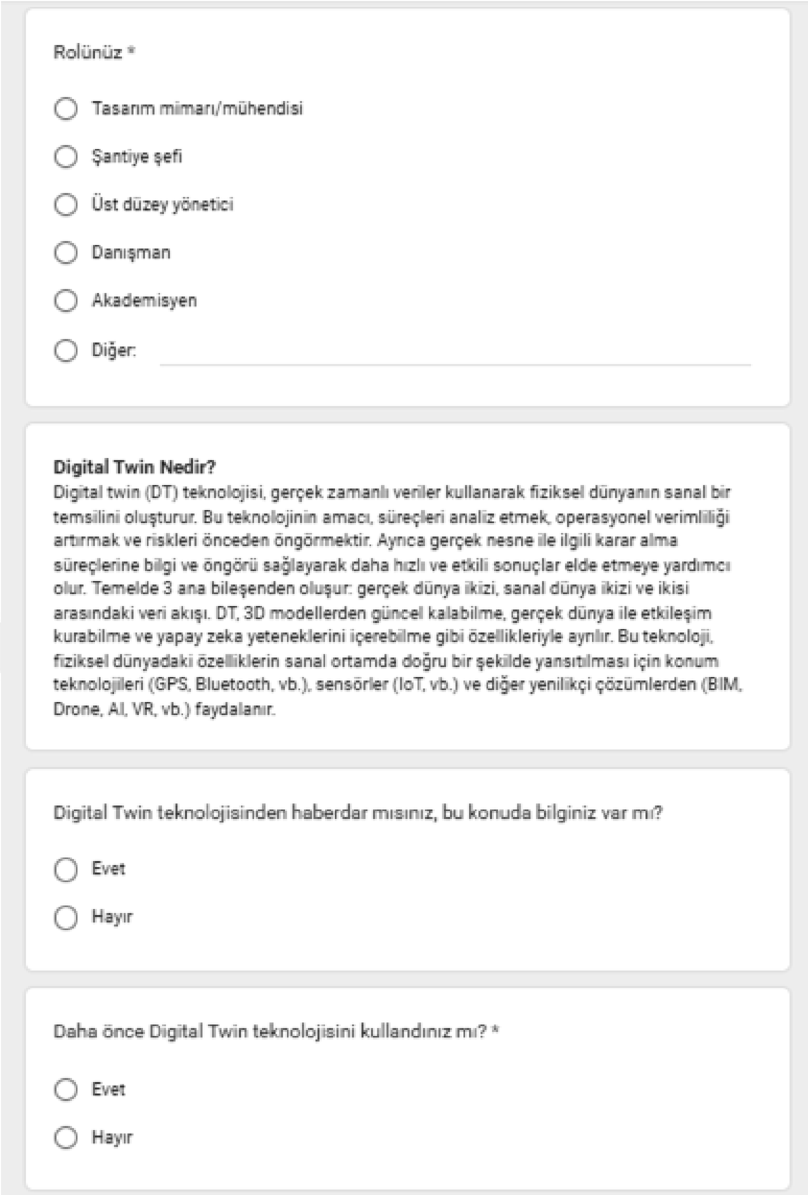
Tecrübeniz *

- 2 yıldan az
- 2-5 yıl
- 6-10 yıl
- 11-15 yıl
- 15+ yıl

Çalıştığınız organizasyon *

- Mimarlık ofisi
- Yüklenici şirket
- Danışmanlık şirketi
- Kalite kontrol ve denetim firması
- Akademi
- Diğer:

Figure A.2 : Questionnaire career information part.



Rolünüz *

- ◯ Tasarım mimarı/mühendisi
- ◯ Şantiye şefi
- ◯ Üst düzey yönetici
- ◯ Danışman
- ◯ Akademisyen
- ◯ Diğer: ____________

Digital Twin Nedir?

Digital twin (DT) teknolojisi, gerçek zamanlı veriler kullanarak fiziksel dünyanın sanal bir temsilini oluşturur. Bu teknolojinin amacı, süreçleri analiz etmek, operasyonel verimliliği artırmak ve riskleri önceden öngörmektir. Ayrıca gerçek nesne ile ilgili karar alma süreçlerine bilgi ve öngörü sağlayarak daha hızlı ve etkili sonuçlar elde etmeye yardımcı olur. Temelde 3 ana bileşenden oluşur: gerçek dünya ikizi, sanal dünya ikizi ve ikisi arasındaki veri akışı. DT, 3D modellerden güncel kalabilme, gerçek dünya ile etkileşim kurabilme ve yapay zeka yeteneklerini içerebilme gibi özellikleriyle ayrılır. Bu teknoloji, fiziksel dünyadaki özelliklerin sanal ortamda doğru bir şekilde yansıtılması için konum teknolojileri (GPS, Bluetooth, vb.), sensörler (IoT, vb.) ve diğer yenilikçi çözümlerden (BIM, Drone, AI, VR, vb.) faydalanır.

Digital Twin teknolojisinden haberdar mısınız, bu konuda bilginiz var mı?

- ◯ Evet
- ◯ Hayır

Daha önce Digital Twin teknolojisini kullandınız mı? *

- ◯ Evet
- ◯ Hayır

Figure A.3 : Questionnaire digital twin information part.


Aşağıdaki faktörlerin yapım aşamasında verimliliği ne derecede etkilediğini düşünüyorsunuz? (1: Hiç etkilemiyor 5: Çok etkiliyor) *

	1	2	3	4	5
İş gücünün yetenek seviyesi					
İş gücünün konuyla ilgili bilgi seviyesi					
İş gücünün motivasyon seviyesi					
İnşaat alanı düzen ve yerleşimi					
İnşaat alanının konumu					
Maliyet yönetim sistemi					
Kalite yönetim sistemi					
Zaman yönetim sistemi					
Malzeme ve ekipman yönetim sistemi					
Yönetimin karar verme yeteneği					
Organizasyonel yöntemler (kurum içi stratejiler)					
Sektördeki finansal belirsizlikler					
Mevzuat değişiklikleri					
Mimari tasarımın inşa edilebilirlik düzeyi					
Mimari çizimlerdeki yanlışlıklar					
Kötü hava koşulları					
Yaşanan yanlış anlaşılmalar					
İletişim engelleri (dil farkları, kültürel engeller					

Figure A.4 : Questionnaire productivity part 1.

Aşağıdaki faktörlerin verimliliği etkilediği durumlarla **ne sıklıkta** karşılaşıyorsunuz? (1: Hiç karşılaşmıyorum 5: Çok karşılaşıyorum) *

	1	2	3	4	5
İş gücünün yetenek seviyesi	○	○	○	○	○
İş gücünün konuyla ilgili bilgi seviyesi	○	○	○	○	○
İş gücünün motivasyon seviyesi	○	○	○	○	○
İnşaat alanı düzen ve yerleşimi	○	○	○	○	○
İnşaat alanının konumu	○	○	○	○	○
Maliyet yönetim sistemi	○	○	○	○	○
Kalite yönetim sistemi	○	○	○	○	○
Zaman yönetim sistemi	○	○	○	○	○
Malzeme ve ekipman yönetim sistemi	○	○	○	○	○
Yönetimin karar verme yeteneği	○	○	○	○	○
Organizasyonel yöntemler (kurum içi stratejiler)	○	○	○	○	○
Sektördeki finansal belirsizlikler	○	○	○	○	○
Mevzuat değişiklikleri	○	○	○	○	○
Mimari tasarımın inşa edilebilirlik düzeyi	○	○	○	○	○
Mimari çizimlerdeki yanlışlıklar	○	○	○	○	○
Kötü hava koşulları	○	○	○	○	○
Yaşanan yanlış anlaşılmalar	○	○	○	○	○
İletişim engelleri (dil farkları, kültürel engeller	○	○	○	○	○

Figure A.5 : Questionnaire productivity part 2.

Projelerin yapım aşamasında **Digital Twin kullanılması**, bu konularda yaşanan sorunların azaltılmasında ne derecede fayda sağlar? (1: Hiç sağlamaz 5: Fazlasıyla sağlar) *

	1	2	3	4	5
İş gücünün yetenek seviyesi	○	○	○	○	○
İş gücünün konuyla ilgili bilgi seviyesi	○	○	○	○	○
İş gücünün motivasyon seviyesi	○	○	○	○	○
İnşaat alanı düzen ve yerleşimi	○	○	○	○	○
İnşaat alanının konumu	○	○	○	○	○
Maliyet yönetim sistemi	○	○	○	○	○
Kalite yönetim sistemi	○	○	○	○	○
Zaman yönetim sistemi	○	○	○	○	○
Malzeme ve ekipman yönetim sistemi	○	○	○	○	○
Yönetimin karar verme yeteneği	○	○	○	○	○
Organizasyonel yöntemler (kurum içi stratejiler)	○	○	○	○	○
Sektördeki finansal belirsizlikler	○	○	○	○	○
Mevzuat değişiklikleri	○	○	○	○	○
Mimari tasarımın inşa edilebilirlik düzeyi	○	○	○	○	○
Mimari çizimlerdeki yanlışlıklar	○	○	○	○	○
Kötü hava koşulları	○	○	○	○	○
Yaşanan yanlış anlaşılmalar	○	○	○	○	○
İletişim engelleri (dil farkları,	○	○	○	○	○

Figure A.6 : Questionnaire productivity part 3.

Digital Twin'in İnşaat Projelerine Faydaları
Digital Twin, inşaat projelerine çeşitli faydalar sağlar. Bunlar şu şekilde gruplandırılabilir:

- Gerçek Zamanlı Dijital Temsil: DT, fiziksel nesneleri sürekli güncellenen dijital temsillerle gerçek zamanlı olarak yansıtır.
- Uzaktan İzleme: Uzmanların her yerden erişebileceği detaylı bilgi ve kontrol imkanı sağlar.
- Kaynak Yönetimi: Malzeme izlenebilirliğini artırır, atıkları azaltır ve iş gücü maliyetlerini optimize eder.
- İş Güvenliği: Tehlikeleri önceden tespit ederek işçilerin güvenliğini artırır ve kazaları minimize eder.
- Risk Yönetimi: Potansiyel riskleri erken tespit ederek anormalliklerin yönetimini iyileştirir ve acil durum planlamalarını güçlendirir.
- Otonom Robotlarla İşbirliği: Robotlarla birlikte çalışır ayrıca robot insan etkileşimini güçlendirir.
- Atık Minimizasyonu: Gerçek zamanlı veriyle sürdürülebilir malzeme ve enerji kullanımı sağlar.
- Öngörüye Dayalı Karar Verme: Simülasyonlar ve yapay zeka desteğiyle bilinçli ve etkili kararlar alınmasını destekler.
- Zaman ve Maliyet Yönetimi: Süreç takibiyle zaman ve maliyet optimizasyonunu kolaylaştırır.
- İletişim ve İşbirliği: Projede paydaşlar arasında uyumu ve verimli iletişimi sağlar.

Bu konu hakkında daha çok bilgiye linkten erişebilirsiniz: Digital Twin'in Faydaları

Aşağıda belirtilen özellikleriyle Digital Twin, verimliliği ne kadar etkiler? (1: Hiç etkilemez 5: Çok etkiler) *

	1	2	3	4	5
Gerçek zamanlı dijital temsil	○	○	○	○	○
Uzaktan izleme	○	○	○	○	○
Kaynak yönetimi	○	○	○	○	○
İş güvenliği	○	○	○	○	○
Risk yönetimi	○	○	○	○	○
Otonom robotlarla işbirliği	○	○	○	○	○
Atık minimizasyonu	○	○	○	○	○
Öngörüye dayalı karar verme	○	○	○	○	○
Zaman ve maliyet yönetimi	○	○	○	○	○
İletişim ve işbirliği	○	○	○	○	○

Figure A.7 : Questionnaire digital twin part 1.

Digital Twin ve Yapım Aşamasında Öne Çıkan Kullanım Alanları

Digital Twin teknolojisinin yapım aşamasındaki kullanım alanları şu şekildedir:

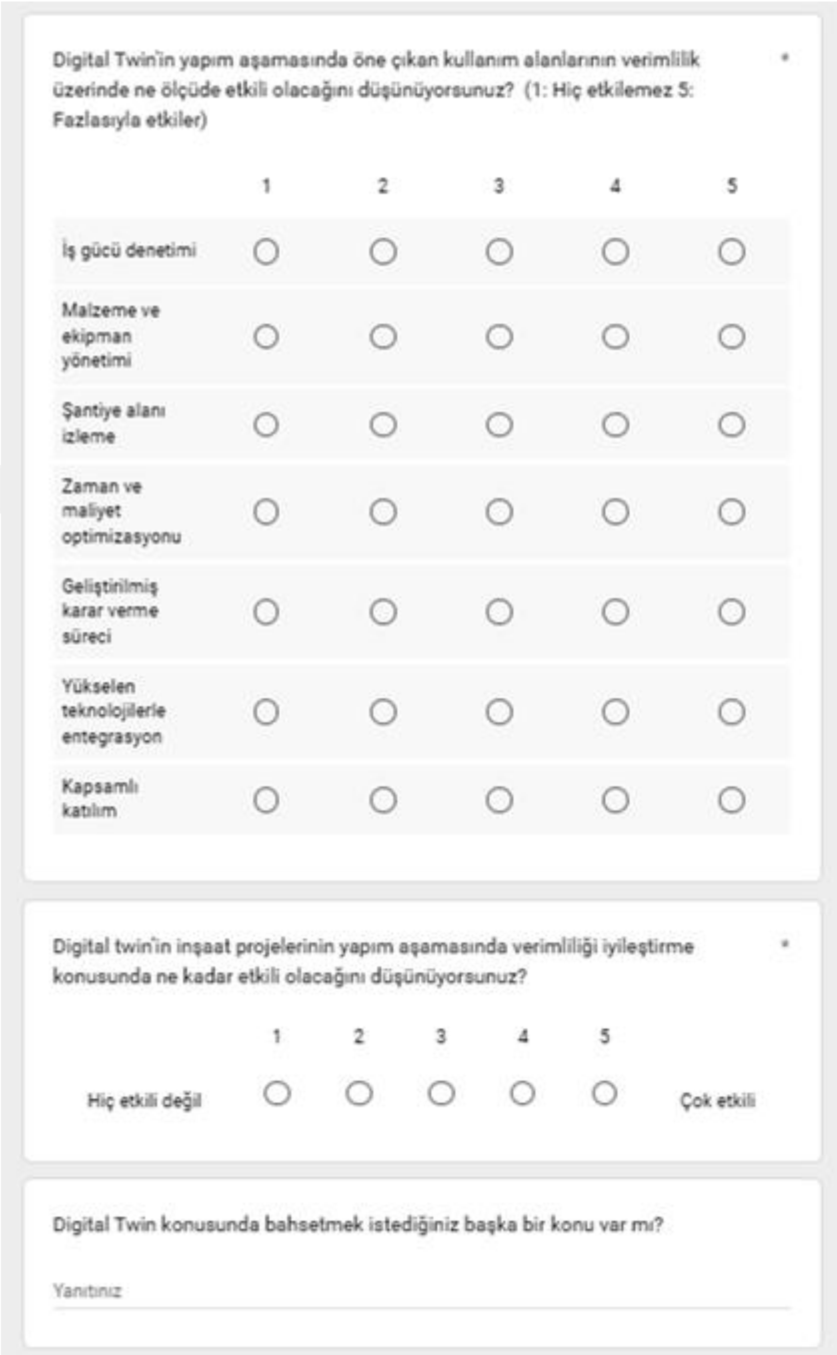
- İş Gücü Denetimi: Dinamik ortamlarda işçi hareketlerini izleyerek iş gücü kontrolünü sağlar ve geri bildirimle kas hareketlerini iyileştirir.
- Malzeme ve Ekipman Yönetimi: Malzeme izleme ve ekipman yönetimini sensörler ve dijital temsiller aracılığıyla iyileştirir, malzeme konumunu izler ve tedarikçi bilgilendirmelerini otomatikleştirir.
- Şantiye Alanı İzleme: İnşaat sahası koşullarını gerçek zamanlı izler ve şantiye sorunlarını hızla çözerek proje takibini iyileştirir.
- Zaman ve Maliyet Optimizasyonu: Tamamlanan görevleri değerlendirir ve bütçe aşımlarını, gecikmeleri öngörerek zaman ve maliyet optimizasyonu sağlar.
- Geliştirilmiş Karar Verme Süreci: İnşaat sürecini gerçek zamanlı izler, tahminler ve simülasyonlarla en iyi kararları almaya yardımcı olur.
- Yükselen Teknolojilerle Entegrasyon: IoT, AI, DL, ML ve diğer teknolojilerle entegre olarak daha kritik bir hale gelir, tahmin ve veri analizi yeteneklerini geliştirir.
- Kapsamlı Katılım: İnşaat süreçlerinde paydaş katılımını artırarak veri paylaşımını hızlandırır ve koordinasyonu iyileştirir.

Bu konu hakkında daha çok bilgiye linkten erişebilirsiniz: DT ve Yapım Aşamasındaki Kullanım Alanları

Digital Twin'in yapım aşamasında öne çıkan kullanım alanlarının verimlilik üzerinde ne ölçüde etkili olacağını düşünüyorsunuz? (1: Hiç etkilemez 5: Fazlasıyla etkiler) *

	1	2	3	4	5
İş gücü denetimi	○	○	○	○	○
Malzeme ve ekipman yönetimi	○	○	○	○	○
Şantiye alanı izleme	○	○	○	○	○
Zaman ve maliyet optimizasyonu	○	○	○	○	○
Geliştirilmiş karar verme süreci	○	○	○	○	○
Yükselen teknolojilerle entegrasyon	○	○	○	○	○
Kapsamlı katılım	○	○	○	○	○

Figure A.8 : Questionnaire digital twin part 2.



Digital Twin'in yapım aşamasında öne çıkan kullanım alanlarının verimlilik üzerinde ne ölçüde etkili olacağını düşünüyorsunuz? (1: Hiç etkilemez 5: Fazlasıyla etkiler) *

	1	2	3	4	5
İş gücü denetimi	○	○	○	○	○
Malzeme ve ekipman yönetimi	○	○	○	○	○
Şantiye alanı izleme	○	○	○	○	○
Zaman ve maliyet optimizasyonu	○	○	○	○	○
Geliştirilmiş karar verme süreci	○	○	○	○	○
Yükselen teknolojilerle entegrasyon	○	○	○	○	○
Kapsamlı katılım	○	○	○	○	○

Digital twin'in inşaat projelerinin yapım aşamasında verimliliği iyileştirme konusunda ne kadar etkili olacağını düşünüyorsunuz? *

	1	2	3	4	5	
Hiç etkili değil	○	○	○	○	○	Çok etkili

Digital Twin konusunda bahsetmek istediğiniz başka bir konu var mı?

Yanıtınız

Figure A.9 : Questionnaire digital twin part 3.

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PUBLICATIONS, PRESENTATIONS AND PATENTS ON THE THESIS:

- **Komar, I., Gunaydin, H. M., & Yalcin, C**. (2024). Digital twin in construction industry: A bibliometric review (Paper ID: 28). In Proceedings of the 8th International Project and Construction Management Conference (IPCMC2024) (pp. 53–62). Yildiz Technical University, Faculty of Civil Engineering. https://ipcmc2024.yildiz.edu.tr/proceedings-book/