

ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

**DIGITAL TWIN FOR ENHANCED CONSTRUCTION PROJECT
MANAGEMENT DURING CONSTRUCTION**



M.Sc. THESIS

Berkay AKTÜRK

Department of Architecture

Project and Construction Management Programme

DECEMBER 2022

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**YAPIM AŞAMASINDA ETKİN YAPIM YÖNETİMİ İÇİN DİJİTAL İKİZ
KULLANIMI**

YÜKSEK LİSANS TEZİ

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To my family and friends,



FOREWORD

This thesis was written for my Master degree in Architecture with specialization in Project and Construction Management at the Istanbul Technical University, Türkiye.

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ABBREVIATIONS

AECO/FM	: Architecture, Engineering, Construction, Operation, and Facility Management
AI	: Artificial Intelligence
ANN	: Artificial Neural Network
AR	: Augmented Reality
BIM	: Building Information Modeling
CAD	: Computer Aided Design
GIS	: Geographic Information Systems
GPS	: Geographic Positioning Systems
IFC	: International Foundation Class
IoT	: Internet of Things
NASA	: National Aeronautics and Space Administration
PhD	: Doctor of Philosophy
RFID	: Radio Frequency Identification
VR	: Virtual Reality



SYMBOLS

N	: Number of Responses
p	: Probability Value
Sig.	: Significance Level
t	: Student t-statistic
α	: Cronbach's Alpha





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DIGITAL TWIN FOR ENHANCED CONSTRUCTION PROJECT MANAGEMENT DURING CONSTRUCTION

SUMMARY

The construction industry has a bad reputation worldwide in terms of productivity and efficiency. Insomuch that, it accounts for a large share of global economic costs. Therefore, a proper management is vital for the construction industry. In order to intensify, increase and improve the quality, value and scope of its management approach, the industry has started to seek the solution in digital tools in recent years. The adoption of Building Information Modeling (BIM) by the construction industry has acted as a spur for the attempt to digitize the industry. Thus, fresher, more sophisticated ideas started to emerge.

The concept of the digital twin, which made its first waves in a space program, has grown rapidly and quickly entered other industries as well as the construction industry, along with the technological trends related to the Industry 4.0. The digital twin is a virtual system that connects design, construction, and operation by using a combination of technologies to data-link its physical and real assets bidirectionally. While the adoption of BIM in the construction industry is not yet complete, the digital twin is considered a closed box for industry professionals and it does not have many practical applications or case studies. At this point, this thesis research aims to shed a light on the interaction of the digital twin and BIM from a construction project management perspective; to investigate the influences of the digital twin during construction.

To answer key questions, -namely (1) “What are the characteristics and practices of the digital twin in the construction industry?”; (2) “What are the functions and applications of the digital twin in the construction from a management perspective?”; (3) “To what extent and how can the digital twin support BIM in the construction?”- a comprehensive synthesis of the literature on the digital twin through the lens of construction project management is carried out as the first step. Scopus database was selected for data extraction by realizing the knowledge gap about the construction, a detailed background analysis was performed to find out the digital twin characteristics, practices, their relationship with BIM, and finally functions and applications of both in construction. As a result of the literature analysis, the topics that can benefit from digital applications within the construction management services provided during the construction phase of the project life cycle are site progress monitoring, resource allocation and waste management, clash detection, decision-making, communication and collaboration, cost management, scheduling, risk management, logistics and supply chain, and safety detection.

As the second step, a questionnaire survey was conducted to measure the influence of digital twin services in the literature on parallel BIM uses intending to understanding the importance of these services for professionals. The first part of the questionnaire captures general information about the respondents and the second part gathers information about the influence of Digital Twin services on BIM uses on a 5-point

Likert scale (1 = not effective, 5 = extremely effective). The study adopted purposive sampling as the sampling method, 108 industry experts were reached and 70 responses were collected with a response rate of 65%.

The data obtained through the questionnaire were analyzed by applying statistical tests through the SPSS 27 program. First, Cronbach's alpha reliability test was used to assess the data's reliability. With a value of 0.893, the study's Cronbach's alpha (α) score was found to be quite acceptable. Secondly, it was observed that the results were normally distributed with the Skewness-Kurtosis normality distribution test, which determined whether the further analyzes would be parametric or not. Third, Pearson's correlation test was applied to measure the relationship between variables. Finally, the variables were divided into meaningful groups in accordance with the aim of the study. Based on experts' opinions, results were analyzed by performing independent-samples t-test and one-way ANOVA.

In the scaling of the influence of the specified digital twin services on parallel BIM uses, all services have received mean scores to be considered high. According to the results, the service with the highest impact on BIM applications was communication and collaboration, while logistics and supply chain and safety detection shared the lowest mean score. These findings suggest that digital twin services during construction have a substantial impact on BIM because they transcend beyond their current uses. Additionally, almost all digital twin services that find applications in construction have a high correlation with each other. This is an indication that elements should be considered as a whole and a two-way network for enhanced management during construction.

By dividing the participants into two groups, whether they are digital twin users or not, and whether they are domestic or international, it was analyzed whether these aspects affected their perspectives by performing independent sample t-tests. Although there was found a statistically significant difference in the "scheduling" variable between domestic and international participants, the fact that both groups had a high mean score showed that the experts thought that the digital twin had a significant impact on 4D BIM applications.

In the first ANOVA test that divided the participants into more than two groups according to their organizational structure, "decision making", "risk management", and "logistics and supply chain" were the digital twin services that have seen a statistically significant difference between groups. Another digital twin service "scheduling", which has seen a significant difference, was observed in analyzes where participants were grouped according to their years of experience. Levene's test was applied to measure the homogeneity of variances related to variables and Games-Howell, Gabriel's and Tukey's post-hoc analyzes were performed to find out which groups caused the identified difference. In addition, even though each group approaches the project with different risks, different objectives and different perspectives, the fact that there are differences of opinion for only a few services in this combination of relationships has been an indication that the positive influence of the digital twin has been accepted by the stakeholders of the industry.

This study reviewed and analyzed the characteristics and current applications of technologies and concepts of the digital twin in the construction industry, and has contributed to and strengthened the digital twin body of knowledge which is limited within the construction project management framework. Additionally, by revealing the topics that digital applications can offer benefits within the construction management

services provided during the construction phase of the project life cycle; the influence and potential of the digital twin on BIM uses have been demonstrated.

Experts agree that digital twin services that offer many uses during the construction go beyond parallel BIM uses and offer several benefits for construction project management. Thus, it has been shown that the digital twin can be a tool for enhanced construction project management, which can get rid of the low efficiency and lack of productivity that the construction industry is still experiencing. This study serves as a source of motivation for researchers working in the field of digital construction and a guide for industry professionals and institutions with question marks about concepts and outcomes.





YAPIM AŞAMASINDA ETKİN YAPIM YÖNETİMİ İÇİN DİJİTAL İKİZ KULLANIMI

ÖZET

İnşaat sektörü, verimlilik ve üretkenlik düzeylerinde dünya çapında kötü bir üne sahiptir. Verimsizliği nedeniyle küresel ekonomik maliyetlerin büyük bir kısmını oluşturan inşaat sektörü, son yıllarda teknolojiye daha adapte ve daha gelişmiş bir yönetim anlayışını benimsemek için çözümü dijital araçlarda aramaya başlamıştır. Yapı Bilgi Modellemesinin (BIM) tüm mimarlık, mühendislik, inşaat, işletme ve tesis yönetimi (AECO/FM) sektörü tarafından benimsenmesi, sektörün dijitalleşmesi yolculuğunda bir katalizör görevi görmüştür. Bu gelişmenin devamında ise daha yeni ve daha sofistike fikirler ortaya çıkmaya başlamıştır.

İlk önemli adımı bir uzay programında atılan dijital ikiz kavramı, uzay aracına ait koşulları sürekli olarak simüle etmek, tahmin etmek, değerlendirmek ve nihayetinde aracın karşılaşılabileceği hataları önlemek için kullanılmıştır. Ardından mevcut sanayi devrimi (endüstri 4.0) kapsamında ses getiren teknolojik gelişmelerle birlikte dijital ikiz, inşaat sektörü de dahil olmak üzere neredeyse tüm sektörlerle hızlı bir şekilde giriş yapmıştır. Dijital ikiz, fiziksel ve gerçek varlıkları çift yönlü bir veri akışı ile birbirine bağlamak için çeşitli teknolojilerin bir kombinasyonunu kullanarak tasarım, yapım ve işletmeyi birbirine entegre eden sanal bir sistemdir. Ancak yapı bilgi modellemesinin bile inşaat sektöründe benimsenmesi henüz tamamlanmamışken; pek fazla pratik uygulamaya veya vaka çalışmalarına sahip olmayan dijital ikiz, inşaat sektörü profesyonelleri için kapalı bir kutu olarak görülmektedir. Diğer taraftan, sektöre adaptasyonları geç başlayan dijital yapım pratikleri kendilerine öncelikle tasarım aşamasında yer bulabilmişlerdir. Bu noktada, bu tez çalışmasının amacı dijital ikiz ve yapı bilgi modellemesi etkileşimine yapım yönetimi perspektifinden ışık tutarak; proje yaşam döngüsünün yapım aşaması özelinde dijital ikizin etkilerini araştırmaktır.

Söz konusu amaca ulaşmak için cevap aranan araştırma soruları şu şekilde ortaya konulmuştur: -(1) "Dijital ikizin inşaat sektöründeki özellikleri ve uygulamaları nelerdir?"; (2) "Yapım yönetimi perspektifinde dijital ikizin yapım aşamasındaki işlevleri ve uygulamaları nelerdir?"; (3) "Dijital ikiz, yapım aşamasında BIM'i ne ölçüde ve nasıl destekleyebilir?". Söz konusu araştırma sorularına cevap bulabilmek için ilk adım olarak, yapım yönetimi merceğinden dijital ikizle ilgili kapsamlı bir literatür araştırması gerçekleştirilmiştir. Yapım yönetimi literatürü tasarım sonrası aşamaların dijitalleştirilmesine ilişkin araştırmaların eksikliğini deneyimlemektedir. Tasarım aşaması veya BIM'den dijital ikize geçişle ilgili çalışmalar literatürde yer alsa da, özellikle yapım süreci için dijital ikiz teknolojisi ve bunun sahadaki kapsamlı uygulanabilirliği hakkında bir araştırma açığı gözlemlenmiştir. Bu bağlamda, Scopus veritabanı üzerinde "dijital ikiz özellikleri", "dijital ikiz uygulamaları", "dijital ikiz ile BIM ilişkisi" ve "yapım aşamasında dijital ikiz ile BIM işlev ve uygulamaları" konu alanında gerçekleştirilen çalışmalar analiz edilmiştir. Analizlerin ardından, literatürde BIM'i daha da geliştirme potansiyeline sahip ve etkin bir yapım yönetimine hitap eden toplam on adet dijital ikiz hizmet tespit edildi. Gerçekleştirilen literatür analizi

sonucunda, proje yaşam döngüsünün yapım aşamasında verilen yapım yönetimi hizmetleri içerisinde dijital uygulamaların fayda sağlayabileceği konular; şantiyedeki ilerlemenin izlenmesi, kaynak tahsisi ve atık yönetimi, çakışma tespiti, karar verme, iletişim ve işbirliği, maliyet yönetimi, süre planlama, risk yönetimi, lojistik ve tedarik zinciri ile güvenlik tespiti olarak belirlenmiştir.

İkinci adım olarak, sektör profesyonelleri perspektifinden yapım aşamasında etkin yapım yönetimi için dijital ikiz kullanımının etkisinin araştırıldığı bir anket çalışması gerçekleştirilmiştir. Anket iki bölüm olarak tasarlanmıştır. İlk bölüm, katılımcıların profili hakkında bilgi almayı hedefleyen soruları içerirken, ikinci bölümde yer alan sorular ile, yapım aşaması için dijital ikiz konseptinin BIM kullanımları üzerindeki etkisini yapım yönetimi bağlamında araştırmak hedeflenmiştir. Anket çalışmasının örnekleme yöntemi “amaca yönelik örnekleme” yöntemiyle belirlenmiştir. Bu bağlamda, 108 sektör uzmanına ulaşılmış ve %65 yanıt oranı ile 70 yanıt toplanmıştır. Anket sonuçları değerlendirildiğinde; katılımcıların %41'i mimar, %30'u inşaat mühendisi ve geri kalan %29'u diğer mesleklerle ilişkili olduğu tespit edilmiştir. Öğrenim seviyelerine bakıldığında, katılımcıların %30'unun lisans, %24'ünün yüksek lisans ve %16'sının ise doktora derecesine sahip olduğu görülmektedir. Katılımcılar, deneyim düzeylerine göre sırasıyla 2 yıldan az (%20), 3 - 5 yıl (%17), 6 - 10 yıl (%22), 11 - 15 yıl (%14) ve 15+ yıl (%27) olmak üzere beş kategoride temsil edilmektedir. Diğer taraftan, katılımcıların bağlı oldukları kuruluşların sırasıyla akademi (%27), işveren/geliştirici (%19) yüklenici (%24) danışmanlık (%30) olarak hizmet verdikleri görülmektedir. Katılımcılardan 35'i Türkiye'de, 35'i ise yurt dışında 24 farklı ülkede çalışmaktadır. Katılımcıların %14'ü BIM yöneticisi, %20'si BIM tasarımcısı, %36'sı üst düzey yönetici, %14'ü akademisyen ve %16'sı sektörle ilgili diğer rollere sahiptir. Daha önce dijital ikiz uygulamalarından herhangi birini kullananların oranı %57 iken, katılımcıların BIM veya dijital ikiz deneyimlerine göre dağılımları şu şekilde sıralanmaktadır: 1 yıldan az deneyimliler (%13), 1-2 yıl deneyimliler (%23), 3-5 yıl deneyimliler (%19), 5 - 10 yıl deneyimliler (%24) ve 10 yıldan fazla deneyimliler (%21).

Anket çalışması aracılığıyla elde edilen veriler SPSS 27 programı aracılığıyla istatistiksel testler uygulanarak analiz edilmiştir. İlk olarak, verilerin güvenilirliğini değerlendirmek için Cronbach alfa güvenilirlik testi kullanılmıştır. 0,893 değeri ile çalışmanın Cronbach alfa (α) değeri oldukça kabul edilebilir bulunmuştur. İkinci olarak, ileri istatistiksel analizlerde parametrik testlerin kullanılıp kullanılmayacağını belirleyebilmek amacıyla normalite testi yapılmıştır. Bu bağlamda, Skewness-Kurtosis değerlerine bakılmış ve verilerin normal dağıldığı tespit edilmiştir. Normal dağıldığı görülen veriler farklı parametrik testler kullanılarak istatistiksel olarak analiz edilmiştir. Bu noktada ilk olarak, anket çalışmasının ikinci bölümünde katılımcılar tarafından değerlendirilmiş olan değişkenler arasındaki ilişkiyi ölçmek için Pearson korelasyon testi uygulanmıştır. Ardından, anket çalışmasına katılan uzmanlar anlamlı gruplara ayrılarak; söz konusu grupların değişkenleri değerlendirmelerinde istatistiksel olarak anlamlı bir farkın olup olmadığı araştırılmıştır. Bu bağlamda ikili gruplar için bağımsız örnekleme t-testi, ikiden fazla gruplar için tek yönlü ANOVA testi uygulanarak, sonuçlar analiz edilmiştir.

Anket çalışmasında literatür araştırması sonucu tespit edilmiş yapım aşamasında verilen yapım yönetimi hizmetleri sıralanmış ve katılımcılardan her bir hizmet bağlamında kullanım bulan BIM teknolojileri üzerinde dijital ikizin etkisinin değerlendirilmesi istenmiştir. Katılımcıların değerlendirmeleri sonucunda her bir servis üzerinde dijital ikizin etki seviyesine ait ortalama değer oldukça yüksek

olduğu görülmüştür. Analiz sonuçlarına göre dijital uygulamalarının en fazla etki ettiği hizmet iletişim ve iş birliği iken; lojistik ve tedarik zinciri ile iş güvenliği algılama konularının diğer hizmetlere göre daha düşük ortalama değer aldığı tespit edilmiştir. Bu bulgular, yapım aşamasında verilen yapım yönetimi hizmetlerinde dijital ikizin kullanılmasıyla BIM uygulamalarına kıyasla çok daha etkin sonuçlar alınacağını işaret etmektedir. Ek olarak, yapım aşamasında dijital ikizin fayda sağlayacağı tüm yapım yönetimi hizmetlerinin birbiri ile ilişkilerinin pozitif yönde ve yüksek korelasyona sahip olduğu görülmüştür. Bu, yapım sırasında ortaya konacak iyi bir yönetimin tüm unsurları bir arada ele alması gerektiğinin bir göstergesidir.

Anket çalışması sonucunda elde edilen verilerin değerlendirildiği bir diğer analiz kapsamında ise bağımsız örneklem t-testi uygulanarak; grupların değişkenlere verdikleri değerlerin ortalamaları karşılaştırılmıştır. T-testi uygulanan ikili gruplar sırasıyla (1) dijital ikiz kullanıcısı olanlar ve olmayanlar ile (2) Türk katılımcılar ve yabancı uyruklu katılımcılar şeklindedir. Analiz edilen değişkenler ise yapım aşamasında dijital uygulamaların fayda yaratacağı yapım yönetimi hizmetleri olarak ele alınmıştır. Sonuçlar değerlendirildiğinde, Türk katılımcılar ve yabancı uyruklu katılımcılar arasında istatistiksel olarak anlamlı bir fark bulunamamıştır. Yalnızca “süre planlaması” değişkeni için istatistiksel olarak anlamlı bir fark bulunsa da her iki grubun da ortalama puanlarının yüksek olması uzmanların dijital ikizin 4D BIM uygulamalarında önemli bir etkiye sahip olduğunu düşündüklerini göstermiştir.

Ayrıca, anket sonucunda elde edilen veriler tek yönlü ANOVA testi uygulanarak analiz edilmiş ve katılımcılar ikiden fazla gruplara ayrılarak, gruplar arasında değişkenlerin aldığı ortalama değerler arasında istatistiksel açıdan anlamlı bir fark bulunup bulunmadığı araştırılmıştır. Tek yönlü ANOVA testinde ilk olarak katılımcıları bağlı buldukları kuruluşlara göre gruplara ayrılmıştır. Analiz sonucunda “karar verme”, “risk yönetimi” ve “lojistik ve tedarik zinciri” gruplar arasında istatistiksel olarak anlamlı farkların bulunduğu değişkenler olarak tespit edilmiştir. Katılımcıların deneyim düzeylerine göre gruplandırıldığı durumda ise, yalnızca “süre planlaması” değişkeninde istatistiksel olarak anlamlı bir fark göze çarpmıştır.. Her iki ANOVA testi sonucunda da tespit edilen anlamlı farkın hangi gruplar arasında olduğunu göstermek ve farkın kaynağını/kaynaklarını ortaya koymak amacıyla post-hoc çoklu karşılaştırma testleri yapılmıştır. Yapılacak post-hoc testini belirleyebilmek için öncesinde değişkenlere ilişkin varyansların homojenliğini ölçmek üzere Levene testi uygulanmış; çıkan sonuçlar doğrultusunda Games-Howell, Gabriel's ve Tukey post-hoc testleri ile gruplar arasında çoklu karşılaştırmalar gerçekleştirilmiştir. Yapılan analizler birlikte değerlendirildiğinde, her bir grubun projeye farklı riskler, farklı hedefler ve farklı bakış açıları ile yaklaşırlar da, sektör paydaşlarının dijital ikizin yapım aşamasında verilen yapım yönetimi hizmetleri üzerindeki pozitif etkisini kabul ettiklerini ortaya konulmuştur.

Bu tez çalışması, inşaat sektöründeki dijital ikiz teknolojilerinin ve kavramlarının özelliklerini ve mevcut uygulamalarını inceleyip analiz ederek; yapım yönetimi perspektifinden ele alındığında oldukça sınırlı bulunan dijital ikiz konu alanındaki literatüre katkıda bulunmuştur. Ayrıca, proje yaşam döngüsünün yapım aşamasında verilen yapım yönetimi hizmetleri içerisinde dijital uygulamaların fayda sağlayabileceği konuları ortaya koyarak; söz konusu hizmetlerin etkin bir biçimde gerçekleştirilmesinde kullanımlar bulan BIM üzerinde dijital ikizin etkisi ve potansiyeli ortaya konulmuştur. Sektör profesyonellerinin, proje yaşam döngüsünün yapım aşamasında verilen yapım yönetimi hizmetleri içerisinde dijital ikiz kullanımının, mevcut durumda kullanılan BIM uygulamalarının ötesine geçtiğini

düşündükleri ve söz konusu dijital ikiz kullanımının etkin bir yapım yönetimi için önemli faydalar sağlayacağı konusunda hemfikir oldukları görülmüştür. Böylece, dijital ikiz kullanımının inşaat sektörünü halen yaşamakta olduğu düşük üretkenlik ve verimsizlik problemlerinden kurtarabilecek etkin bir yapım yönetimi için bir araç olabileceği gösterilmiştir. Bu çalışmanın, dijital yapım alanında çalışan araştırmacılar için bir motivasyon kaynağı; kavramlar ve kazanımlar konusunda soru işaretlerine sahip sektör profesyonelleri ve kurumlar için ise bir rehber niteliğinde olması ise çalışmanın pratik alana sağlayacağı bir diğer katkı olarak değerlendirilmektedir.



1. INTRODUCTION

The construction industry has a bad reputation worldwide in terms of productivity and efficiency. The McKinsey Global Institute's report in 2017 estimates that the construction industry's inefficiency costs the world economy about 1.6 trillion dollars. The report also claims that regions and companies that adopt digital technologies and have better management understanding can increase productivity by 50 to 60 percent. Clearly, to get rid of this bad reputation, the construction industry has to intensify, increase and improve the quality, value and scope of its management approach. Throughout history, industrial revolutions facilitated and enhanced management approaches as well as production processes. The idea of the current industrial revolution, known as Industry 4.0, is to link physical settings with digital eco-systems (Sepasgozar, 2021). Manufacturing industries, whose current studies are on the digital twin, have been looking for solutions in information technologies for many years to overcome their management problems (Cimino et al., 2019). According to Kivrak et al. (2013), many people believe that an organization's reliance on information technologies in the twenty-first century is comparable to its reliance on electricity in the one before it. Through advancements in information technologies, analogue, mechanical, and electronic technology were replaced by digital technology in the new information era, and these technologies have since turned into an active value proposition for increasing productivity (Ozturk, 2021).

With the increasing complexity of projects, competition, changing client demands, new generation employees and stakeholders as time goes by, the construction industry face a wide range of difficulties that negatively effects the construction process. So, the construction industry has also started to seek the solution in digital tools in recent years to adopt a progressive management approach that adapts to technology, following manufacturing industries to increase its efficiency and productivity to accomplish more high-quality results in less time and with less money (Silva et al., 2021). The automation of conventional manual operations, made possible by the development of digital technologies like Building Information Modeling (BIM),

Internet of Things (IoT), mobile devices, drones etc., has been the driving force behind improvements in performance, productivity, and safety in the construction industry (Rodrigues et al., 2022). As one of the biggest steps taken in this journey in the industry, the adoption of Building Information Modeling by the entire construction industry has acted as a catalyst for supporting the digitalization effort. Unfortunately, although the construction industry provided a late but rapid adaptation by integrating digital tools into pre-construction processes and getting very positive results, it could not provide these developments to the same extent in the post-design stages. Construction project management literature studies related to the design phase or transition from BIM to digital twin exist, a knowledge gap has been observed regarding the digital twin technology in post-design phases and its broad applicability in the field, especially for the construction process.

BIM is a method of using a digital 3D representation of a structure to facilitate the management of itself and all its assets mainly in the early phases of the building life cycle. The BIM concept shows up through a life cycle of digital information (Silva et al., 2021). The primary thing that distinguishes a BIM model from a 2D drawing is that the structure is approached not with lines, but with a combination of components. All assets covered in the model might be processed with information like specification, installation, or construction method, not only geometric dimensions. BIM models can be defined with 4D to 7D dimensions depending on the data (schedule, cost estimation, maintenance management, energy information) integrated into them, which determines the benefits that can be derived.

Goyal et al. (2020) defined BIM, as designing, constructing, operating, and managing a facility in time and cost-efficient ways by providing information exchange to stakeholders with the help of an information-rich 3D model. This smart resource model facilitates the management of each phase of the construction by hosting the necessary information. The potential of merging the BIM model with other technological breakthroughs to create a complete replica or digital twin of any given built asset has just recently been discovered by industry participants.

Khajavi et al. (2019) noted that there are two key distinctions between BIM and the digital twin. The first key distinction is, the digital twin is intended to monitor a physical asset, whereas BIM was created to increase efficiency in the early phases of the building life cycle. The second key distinction is that digital twins operate in

opposition to the current BIM platform because BIM was not created to work with real-time data, while digital twin is the digital counterpart of a physical asset. However, since the virtual model is the basis of the digital twin concept, a BIM model of the structure prepared during the design phase can be the first step in creating a digital twin.

A building's digital twin can be defined as a process that allows for the interaction of a physical building's environment with a digital but accurate virtual version of it to gather and monitor data in real-time. Deng et al. (2021) define the purpose of using the digital twin in the construction industry as ensuring smooth management by synchronizing the physical asset in the real world with a virtual platform, with objectives such as control of the construction, facility management, scene monitoring, and other life cycle processes in the built environment. The digital twin concept can be achieved by data exchange between a physical object and a virtual representation of it, so it is necessary to collect, filter and process raw data in various ways and with a variety of data-related tools and modeling and simulation technologies.

Although the digital twin is a different concept from BIM, it provides various benefits and applications for construction project management by transforming the smart model provided by BIM into a virtual replica that provides instant data, supported by a variety of technologies. Especially the digital twin services facilitating the management of the project during construction seem to intersect with the BIM uses in the industry (Boje et al., 2020; F. Jiang et al., 2021; Opoku et al., 2021). However, there are different levels of benefits and effects.

1.1 Aim and Objectives

The digital twin is a virtual system that links design, construction, and operation by bidirectionally data-linking its physical and real assets utilizing a variety of technologies. Although BIM adoption in the construction industry is still not complete, the digital twin is regarded as a closed box by industry insiders since it lacks many real-world applications and case studies. At the same time, the construction and project management literature has a lack of knowledge in the field of digitalisation for the post-design phases. Having experienced in other industries, it is quite clear that the construction industry must enhance its management understanding to have better numbers. In this direction, this thesis research aims to shed a light on the interaction

of the digital twin and BIM from a construction project management perspective; to investigate the influences of the digital twin during construction.

Therefore, this study sought answers to three research questions.

- “What are the characteristics and practices of the digital twin in the construction industry?”
- “What are the functions and applications of the digital twin in the construction from a management perspective?”
- “To what extent and how can the digital twin support BIM in the construction?”

1.2 Methodology

To meet the objectives, this study is conducted in two parts. While the first part is a comprehensive synthesis of the literature on the digital twin through the lens of construction project management, in the second part, a quantitative questionnaire survey was created with the digital twin services that can go beyond BIM and address an enhanced construction project management. The data obtained through the questionnaire survey were analyzed by applying statistical tools.

1.3 Scope

The scope of this master's thesis is to follow the digitalization journey of the construction industry, to reveal the reflections of the latest technological developments from the perspective of construction project management, to explain and evaluate what they are, how they work, and how they can be adapted to provide enhanced construction project management approach.

1.4 Structure

The thesis contains five chapters. In the first chapter, background information, aim and objectives, methodology, and structure of the research are given.

The second chapter is a comprehensive synthesis of the construction project management literature on digital twin characteristics, practices, their relationship with BIM, and finally functions and applications of both in the construction.

The third chapter, named research methodology, is dedicated to explain the scientific framework around the research. It outlines the actions taken for the literature synthesis, sample selection, questionnaire structure, and procedures to evaluate the questionnaire.

After methodology and the research description, in chapter four, gathered research data is introduced and statistical tests are employed for further analysis.

Finally, the fifth chapter includes discussion and conclusion. A summary of the research is provided, and then the main results and discussion is presented.





2. LITERATURE REVIEW

2.1 Digital Twin

The phrase "digital equivalent to a physical product," which is generally regarded as the initial definition of DT, was first used in 2003 at the University of Michigan (M. W. Grieves, 2019; Opoku et al., 2021). Although the emergence of the concept of the digital twin is not very new, recent technological developments within the scope of the current industrial revolution (industry 4.0) and trends such as cloud computing, smart sensors, 3d printing, autonomous applications, and artificial intelligence assistance, the use of which are rapidly increasing, have brought the concept under the microscope by different disciplines and led to new definitions (see Table 2.1).

Table 2.1 : Definitions of the digital twin in the literature

Definitions	References
A simulation, result, or depiction of real-world physical elements.	(Ni et al., 2021)
A real-time updated as-built information model.	(J. Li & Kassem, 2021)
A system built on the fusion of physical and digital components.	(Mannino et al., 2021)
A virtual representation of a physical structure used to produce advanced simulation results.	(Schöberl et al., 2020)
A digital depiction of an interesting physical object.	(Cimino et al., 2019)
An integrated simulation of a system that reflects its identical twin using physical models and sensor updates.	(Glaessgen & Stargel, 2012)
A digital replica of physical assets, processes and systems.	(Vivi et al., 2019)
A computerized and mirror representation of the production process itself.	(Pan & Zhang, 2021)
A perfect representation of a physical object in a virtual environment.	(Y. Liu et al., 2021)

According to Pan & Zhang (2021), one of the important factors that increased the interest in the digital twin concept is the work done by the National Aeronautics and

Space Administration (NASA) aimed at continuously monitoring the instant data of the spacecraft. To evaluate vehicle condition, make predictive decisions via simulations, and reduce errors. NASA's decision to create a replica of the spacecraft in a digital environment to achieve the targeted results in its work reveals the main logic of the digital twin concept. A digital twin is the simultaneous and one-to-one existence of a real physical entity in a digital environment by providing data flow with the help of several technologies. In this way, a system with a clearer monitoring environment and a safer framework for decisions to be made is created, especially for assets that carry critical risks in terms of danger, cost, time, etc. As can be seen from the definitions in Table 2.1 and the previous explanations, the digital twin concept is a continual and bidirectional data stream between a physical asset and its virtual representation as shown in Figure 2.1. Accordingly, a digital twin system is embodied in three main elements:

1. A physical entity in the real world
2. Its virtual counterpart in a digital environment
3. Data flow that connects both.

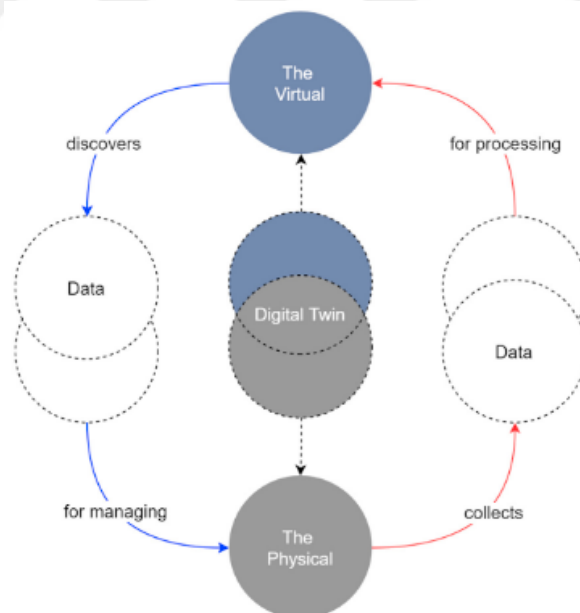


Figure 2.1 : The Digital Twin paradigm (Boje et al., 2020)

Cumo (2021) explained the core parts of the digital twin with 4 concepts: (1) Models, functions like creating an exact clone of the physical part, generating stimulated behaviors to follow while acting on the physical part, working autonomously in the digital counterpart, forecasting issues, creating preventative strategies, and evaluating

performance; (2) Data, it is the information that enables the digital twin to operate continually; (3) Connections, which enable interaction between the various DT elements (within physical part, within virtual counterpart, and between physical and virtual); and (4) services such as prediction, evaluation, and validation.

Yitmen et al. (2021) state that dynamic mapping in digital twin takes place by examining and collecting data from the real entity in the physical world and sending it to the virtual world for analysis. The authors added that the virtual twin provides simulation, prediction, and optimization opportunities with data learned from various sources, providing fast solutions, accurate reactions, and full-content guidance for real processes. A sensor network and a physical asset are needed for a digital twin, although neither is needed for simulation, which is the primary distinction between the two (Khajavi et al., 2019). There are two more subclasses to better describe some projects that don't quite fit the definition of a digital twin. First, there is the Digital Model, which is like a BIM when used in the construction industry and refers to a digital representation without automatic data transfer; second, there is the Digital Shadow, which only uses automatic real-time data transfer from the physical to the digital asset (Coupry et al., 2021). As it turns out, the connection between “physical” and “virtual” entities is provided by forms of "data" from various sources. To put it another way, the physical part collects real-world data that is still raw and has to be processed, while the virtual part reflects the same data into the physical, making it processable and storable with the help of various engineering applications and technologies such as artificial intelligence as shown in Figure 2.2. To manage the usage of the physical daily (Boje et al., 2020; M. Grieves, 2014).

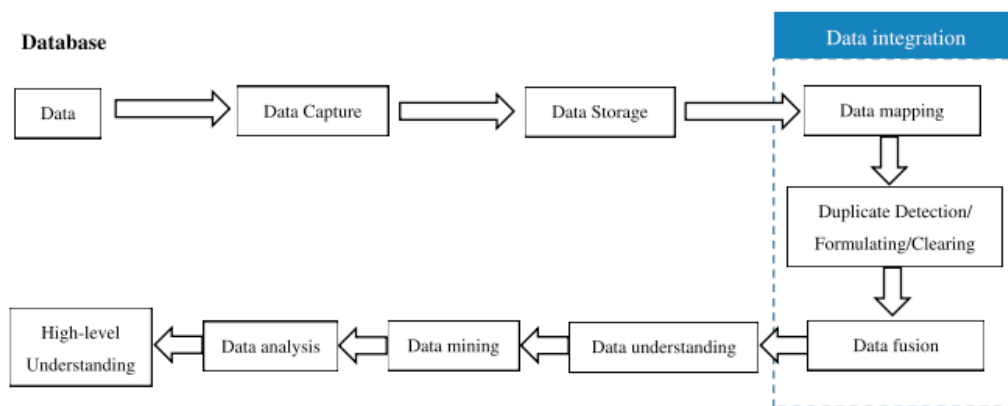


Figure 2.2 : Data processing map from raw data to high-level understanding (J. Zhang et al., 2021)

According to Chen & Huang (2020), a digital twin can be digital copies of physical assets, processes, people, equipment, or systems for various purposes (see Figure 2.3). The authors also added that technologies such as the internet of things, artificial intelligence, and machine learning are used according to the purpose, while they are used in different industries such as the smart city (urban data collection and modelling), the health industry (expose and situation tracing) and the manufacturing industry. The diversity and level of data collected and the technologies used to determine the purposes, opportunities, and outputs of the digital twin. Madni et al. (2019) described five different levels of the digital twin, depending on their developmental level (Shahzad et al., 2022). A level 1 digital twin is a typical prototype made for engineering purposes that aids in concept-stage decision-making. Historical and maintenance data and operational performance from the physical asset can be included in level 2. A level 3 is an adaptive digital twin that has an adaptive user interface for the digital and physical parts. This type of digital twin can learn the operator's priorities and preferences in a variety of contexts and is constantly updated based on the data it receives from the physical component in real-time. An intelligent model with level 3 functionalities that can self-learn without supervision is referred to be a level 4 digital twin. Last but not least, a level 5 model is open to the information offered by outside sources and analyzes the information for analysis in a situational context.

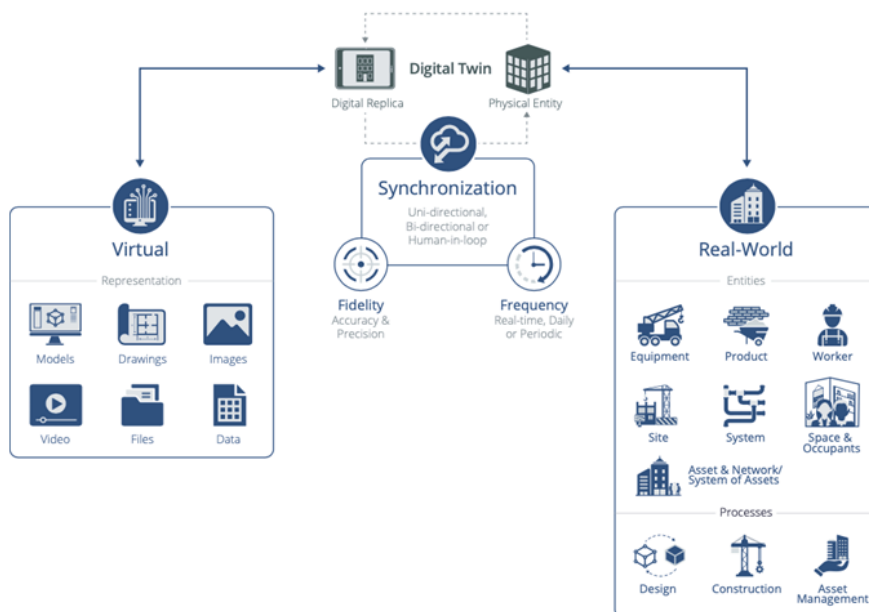


Figure 2.3 : Elements of a digital twin (RICS, 2022)

Salem & Dragomir (2022) noted that digital twins have a significant number of advantages and uses: By running tests utilizing information from the operating environment, they can validate and confirm the integrity of a system model and then make assessments, improvements, and forecasts; they can support decision-makers' decisions based on reports from the digital part regarding the project that will be put into practice in the physical part; as a result of the digital part's ability to analyze and simulate processes, they can anticipate future changes in the physical part and create the necessary plans; the twin can disclose extended visions and major gains for the outcomes of the real-world system, so they can use simulation to find practical opportunities to add to the physical part. The main application areas of the digital twin can be classified as electric power generation, infrastructures, city management, construction, security, and emergency (Cumo, 2021). The concept of the digital twin is prominently included in the manufacturing literature to explain product lifecycle management practices such as the follow-up of the design, production, operation, and destruction phases of the product's journey (Camposano et al., 2021). In addition, Ozturk (2021) also stated that the most common application area of the digital twin concept is product lifecycle management and it can be considered newer to the architecture, engineering, construction, operation, and facility management (AECO/FM) literature. Which has a similar complex value chain that needs to be under control and monitored at any phase.

2.1.1 Digital Twin in Construction

A building's digital twin can be defined as an interaction between the environment of a physical building and a digital but accurate virtual representation of that environment, enabling real-time data collection and monitoring (Khajavi et al., 2019). Camposano et al. (2021) have brought together seven metaphors used by AECO/FM practitioners to describe the digital twin: a lifecycle representation; a process modeling method; a visualization tool or user interface; the convergence of the physical and the digital world; an IoT data platform; a shared concern between different communities of practice; and a service ecosystem. Deng et al. (2021) define the purpose of using the digital twin in the construction industry as ensuring smooth management by synchronizing the physical asset in the real world with a virtual platform, with objectives such as control of the construction, facility management, scene monitoring, and other life cycle processes in the built environment. In a recent review of the

construction literature, it has been revealed that the digital twin concept has applications in all life cycle processes in the built environment, except for the demolition phase (Opoku et al., 2021). Considering once again that the digital twin concept can be achieved by data exchange between a physical object and a virtual representation of it, it is necessary to collect, filter and process these raw data in various ways for the construction industry as well as in other areas of use. Opoku et al. (2021) also stated that as a prerequisite for digital twin applicability, various data-related tools, modeling, and simulation technologies that work with precise details and have high accuracy are needed for data collection and processing. When the literature on the digital twin is examined within the framework of the construction industry, tools that can collect data in different formats such as tags, sensors, gauges, unmanned aerial vehicles and drones, laser scanners, cameras, etc., are shown as examples of widely used data sources, while some technologies used in analyzing and putting data into use and offering a variety of advantages. Pour Rahimian et al. (2020) analyzed the data gathering tools used in the construction industry in three main categories: first, enhanced information technologies such as email, audio, and multimedia; second, geospatial technologies such as geographic information system (GIS), geographic positioning system (GPS), barcoding and RFID (radio frequency identification); and finally, image-based technologies such as photogrammetry and laser scanning. The adaptation of the digital twin concept to the construction industry has come to the fore with the developments in the industry during the digitalization process. BIM methodology, which has been one of the cornerstones of the digitalization process of the construction industry in the last decades, has led to the adoption of Industry Foundation Classes (IFC) technology, which will pave the way for the use of common data to increase interoperability and facilitate processes. According to Boje et al. (2020), the evolution of data sharing and integrated systems, which are rapidly adopted and widespread in the construction industry, depends on the emergence of IFC technology.

2.1.2 Building Information Modeling (BIM)

Contrary to what is often confused in the industry, BIM is a methodology, not a technology. It is a method of using a digital 3D representation of a structure to facilitate the management of itself and all its assets throughout all construction processes such as design, construction, operation, maintenance, and demolition. The primary thing

that distinguishes a BIM model from a 2D drawing is that the structure is approached not with lines, but with the combination of components such as walls, floors, doors, and windows. When the BIM methodology is desired to work in accordance with its purpose and to be efficient, it is not enough to keep the 3D representation used only in geometric dimensions. All assets covered in the model might be processed with information like specification, installation, or construction method. Considering that 3D is only geometric dimensions, BIM models can be defined with 4D, 5D, 6D, or 7D dimensions depending on the data (schedule, cost estimation, maintenance management, energy information) integrated into it (Agostinelli, Cinquepalmi, et al., 2019; Agostinelli, Ruperto, et al., 2019; Khajavi et al., 2019; I. O. Onungwa et al., 2017). The integrated data determines the benefits that can be derived from a project built with the BIM methodology. Silva et al. (2021) stated that the concept of BIM is realized through a digital information life-cycle from the conceptual design of the building to its demolition. To improve planning, construction, and maintenance throughout a facility's life cycle, it serves as a platform for maintaining an accurate and interoperable record of building information (Khajavi et al., 2019). Considering that it will facilitate the management of each of the construction processes, it acts as a smart resource model by hosting the information such as manufacturer, material, price, and procurement of the components of the building and the plans such as logistics and schedule of the project. Thus, with the use of BIM, the construction process can be virtually represented, the cost and resource allocation can be simulated, the construction plan can be continuously updated, and the construction's rationality can be strengthened (Y. Jiang, 2021).

Goyal et al. (2020) defined BIM, as designing, constructing, operating, and managing a facility in time and cost-efficient ways by providing information exchange to stakeholders with the help of an information-rich 3D model. The authors stated that cooperation, such as unifying and coordinating the construction activities in the project, is through the sharing of information through interaction, communication, exchange, and coordination. BIM lays the groundwork for a close collaboration between clients, designers, and contractors (Wong et al., 2020). According to Khajavi et al. (2019), the main emphasis of BIM is that the model is not only information-embedded, but also the model can provide an enhanced interdisciplinary collaboration environment for the AECO/FM industry. The possibility that more than one discipline,

such as a designer, civil engineer, or mechanical engineer, can work simultaneously on a single BIM model throughout the life-cycle of the building, eliminates communication issues and provides the aforementioned interdisciplinary collaboration environment. Starting from the 2D geometric lines, the BIM model is divided into BIM proficiency stages according to the information level of the assets and plans it contains i.e., material, specification, volume or supply, cost, and schedule (Wong et al., 2020). As presented in Table 2.2

Table 2.2 : BIM proficiency levels (Wong et al., 2020)

Level	Definition
Level 0	Unmanaged 2D CAD drawings containing lines, arcs, and text, with paper.
Level 1	Managed 2D and 3D CAD with a collaboration tool providing a common data environment.
Level 2	Managed 3D environment held in separated discipline BIM tools with minor integration of 4D and 5D elements.
Level 3	Fully open process and data integration between all disciplines using a single shared project model which is held in a centralized repository.

As understood in the definition of Level 3 in Table 2.2, the point that the AECO/FM industry is trying to reach in BIM methodology is the interoperability of more than one discipline on a single model. However, this is where the differences in file formats come into play. As in the third level of BIM, also it is mentioned in the literature that the data transformation problem should be well resolved to develop smart city or digital twin studies (Zhu & Wu, 2021). Fortunately, the creation of the Industry Foundation Classes (IFC) framework has enhanced interdisciplinary cooperation in the AECO/FM industry on a global scale (I. Onungwa et al., 2021).

Industry Foundation Classes (IFC)

The International Alliance for Interoperability created a standard for specifying the object representations for construction projects (I. Onungwa et al., 2021). IFC, a neutral data format for representing the BIM model, was introduced in 1994 as an open standard data model used for the integration and exchange of BIM data in the buildingSMART portfolio. It is supported by many BIM applications and tools to describe, transfer, and share all building information like geometry, aspects, quantity,

etc. (Mirshokraei et al., 2019; Sharafat et al., 2021; Zhu & Wu, 2021). IFC is perfect for addressing the issue of application interoperability. It provides a universal standard for data exchange: For example, the building model developed by Revit can be exported to an IFC software using the IFC format, just as you can import an IFC file in Revit and develop a model by creating an RVT file (I. Onungwa et al., 2021; Autodesk, 2019). IFC schema is the most suited and essential data format for wider BIM adoption and information integration because of its flexibility and consistency throughout the construction lifecycle (Lu et al., 2020). As one of the potentials of this format, a 4D BIM model can be obtained by exporting the model to a suitable software to prepare the timeline of the project, identify the relevant actors, and assign the physical elements to the worksheet (Mirshokraei et al., 2019). But the transfer of this kind of information is still challenging. Boje et al. (2020) state that combining several modeling documents (in various formats) that develop concurrently might result in conflicts and interruptions that could be considerably reduced by automation and linked data. To enable IFC-based interoperability between BIM and other data sources, the data structure in the data/model integration layer of digital twins is created to be able to exchange and interact with external data (Lu et al., 2020).

2.1.3 Comparison of BIM and Digital Twin

According to Camposano et al. (2021), industry players have more recently begun investigating the potential of combining BIM technologies with other technological advancements to produce a complete duplicate or digital twin of any given built asset. Authors also argue that when AECO/FM stakeholders place higher expectations on BIM and other associated technologies, digital twins are sophisticated software ecosystems that result from these demands. Digital twins and BIM have some conceptual overlap, as noted by Shahzad et al. (2022). They identified three common interpretations seen in the literature: (1) digital twin as a development and continuation of BIM; (2) BIM and digital twins are two unique ideas due to several clear differences; (3) BIM and digital twins are two complementary concepts that can be used to enhance one another.

Khajavi et al. (2019) noted that there are two key distinctions between BIM and digital twin. The first key distinction according to their research is, the digital twin is intended to monitor a physical asset, enhance its operating efficiency, and enable predictive

maintenance, whereas BIM was created to increase efficiency in the design and construction phases of the building life cycle. The second key distinction is that digital twins operate in opposition to the current BIM platform because BIM was not created to work with real-time data, while digital twin is the digital counterpart of a physical asset. A similar situation is emphasized by Tang et al. (2019), saying that without additional data sources, BIM can only supply static data about the built environment and cannot automatically update real-time information on models. Jiang et al. (2021) presented the mentioned comparison, as follows:

- 1) A virtual model is necessary for both a digital twin and a BIM model.
- 2) A BIM model does not place as much emphasis on the physical counterpart as a digital twin does.
- 3) An object that does not exist or has not yet been constructed may be represented by a BIM model. Contrary, the current status of the physical counterpart must be promptly reflected in a digital twin.
- 4) A digital twin stresses linkages with the physical part. While BIM or "as-is" BIM does not.

BIM is mainly used to avoid errors during the design stage, aid communication between parties, enhance efficiency, and examine the project's time and cost information. Concurrently the digital twin of a building can be used for predictive acting, better allocation of resources, what-if analysis, etc. (Khajavi et al., 2019). To convey the differences in detail, Table 2.3 provides a comparison of the characteristics of BIM and digital twins based on information from the literature (Shahzad et al., 2022). The virtual model is the basis of the digital twin. A custom 3D model or a 3D CAD model taken from BIM can be used for digital twin visualization. But it has become clear that a BIM model of the structure prepared during the design phase can be the first step in creating a digital twin, considering that there are as many commonalities as there are differences between BIM and digital twin.

Table 2.3 : Characteristics of BIM and digital twin (Shahzad et al., 2022)

Characteristics	BIM	Digital Twin
3D modeling	+	+
Real-time virtual model	-	+
Live model updates through sensors	-	+
Data exchangeability between virtual and physical models	-	+
Data standardization	+	+
Scheduling	+	+
Major contribution at the design stage	+	+
Contribution at the construction stage	+	+
Major contribution at the operations stage	-	+
Increased collaboration	+	+
Time management	+	+
Cost management	+	+
Project simulation analysis	+	+
Project simulation analysis in context with surroundings	-	+
Live monitoring of assets	-	+
Live and instant updates on equipment status	-	+
Instant response to equipment failures	-	+
Realistic predictive maintenance	-	+
Getting insights to improve building utilization and performance	-	+
Reduced project time and cost over the project lifecycle	+	+
Easy application on existing buildings	-	+
Better value for employers	+	+
Improved building sustainability	+	+
Improved dynamic risk management at the construction site	-	+
Enhanced site logistics	-	+
Updated data for operation and maintenance purposes	-	+
Use of machine learning and automated processes	-	+
Use of self-learning algorithms	-	+
Necessary use of common data environment	-	+

Zhang et al. (2021) considered BIM an essential key to creating a digital twin, as it creates information models that correspond to the target components and gathers data about those components. Figure 2.4 shows essential components such as BIM and various sensor networks that the digital twin uses to create a real-time image of the structured entity. This dynamic structure provides real-time analytics, enhanced decision-making, increased building effectiveness, and comfort (Khajavi et al., 2019). In the AECO/FM industry literature, the integration studies of IoT and similar technologies with BIM played an active role in the emergence of this view (Alizadehsalehi & Yitmen, 2016; T. Han et al., 2022; Zhen Liu et al., 2019; Ni et al., 2021; Park et al., 2016; Qian, 2021; Reinbold et al., 2019; Smaoui et al., 2018; Tang et al., 2019).

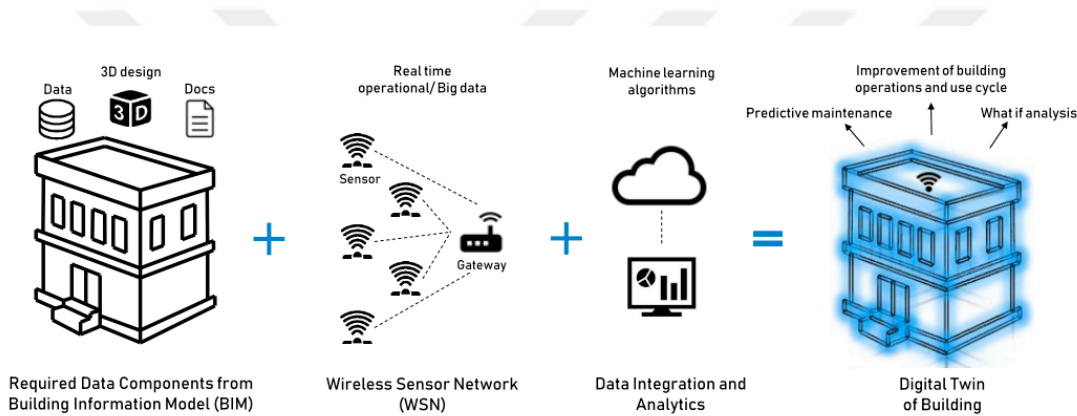


Figure 2.4 : Essential components to create a digital twin of building and difference with BIM (Khajavi et al., 2019)

Deng et al. (2021) presented research examining the transition from BIM to digital twin applications. The authors discussed the evolution of BIM into a digital twin at 5 different levels as in Figure 2.5, stating that the visualization and analysis of real-time environmental data with the help of smart devices such as IoT became available in BIM models, and the automatic updating of BIM models according to real-time building status led to the emergence of a digital twin. Khajavi et al. (2019) also noted that efforts are underway to enable BIM to take advantage of real-time data inputs from sensors and IoT devices.

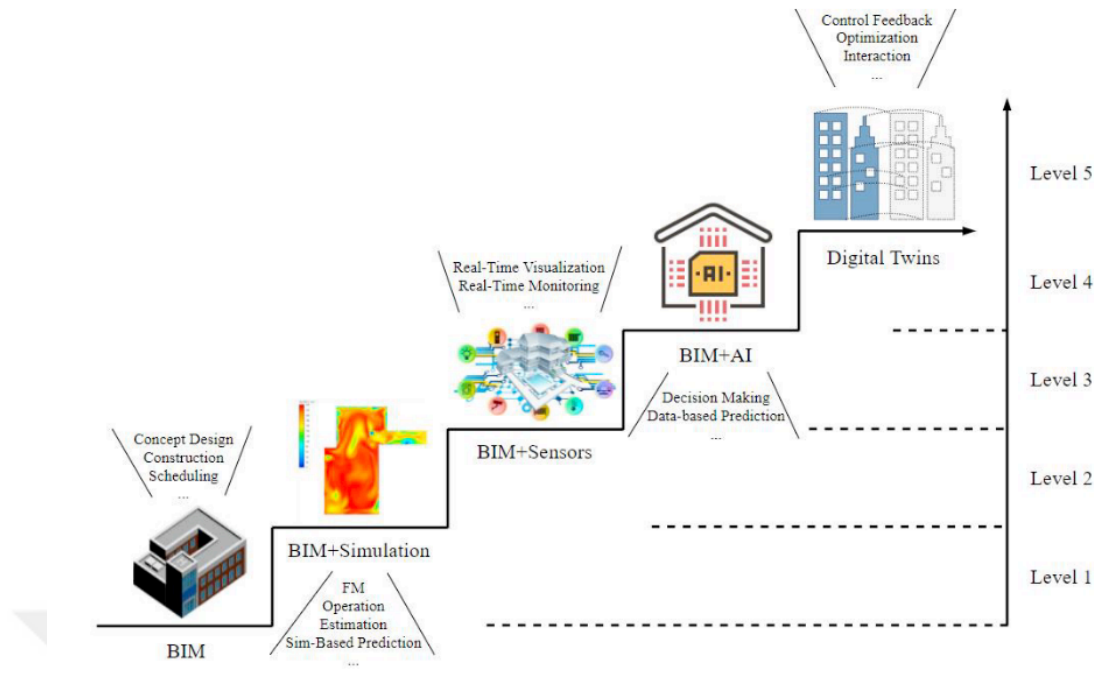


Figure 2.5 : Evolution of BIM to digital twins in the built environment (Deng et al., 2021)

While the use of BIM in the creation of digital twins continues with a natural structure by offering a ready-made 3D information model, unknown benefits in this method have begun to emerge as the use of digital twins in the industry increases. Coupry et al. (2021) compiled 17 studies to identify the benefits uncovered in creating a digital twin based on BIM they stated that a BIM-based digital twin can be compared to a centralized database where the static data, such as maintenance records and technical documents, are linked to an equipment's 3D representation to make retrieval easier when needed. In their research, the authors of the study revealed benefits like improvement of current building lifecycle operations, such as advancing equipment usage or reducing costs, optimization of the building construction, and exploitation such as reducing energy use or carbon emission by ontological information provided that BIM provides. A digital twin could be created and used for routine monitoring and maintenance tasks through the use of a central collaborative network if a building information model is specially created to accommodate information in a 3D model with additional information like equipment specifications, cost estimations, or schedules (Shahzad et al., 2022). The efforts to develop BIM, caused by the problems faced by the construction industry in terms of productivity and efficiency, and by the technological developments in other industries, have also been reflected in academic studies (see Figure 2.6). Using BIM to create a digital twin is the process of integrating

new technological developments and concepts of industry 4.0 into the digital model. This improves existing uses of BIM and unlocks new benefits and uses with the digital twin.

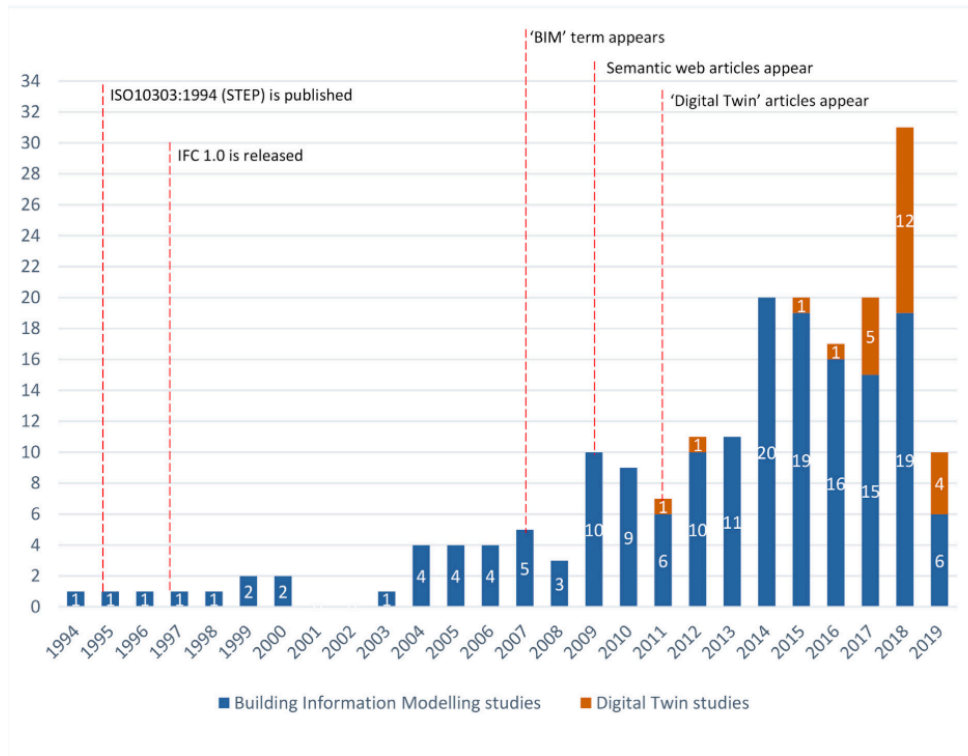


Figure 2.6 : Distribution of reviewed papers by publication date with important milestones in the construction industry (Boje et al., 2020).

2.1.4 Digital Twin Technologies: Definitions, characteristics, and applications

Cumo (2021) cited the construction industry as one of the application areas of the digital twin and stated the application titles as progress monitoring, work schedule and budget adjustment, resource allocation and waste tracking, safety monitoring, quality assessment, and improving usage rate for equipment. Shahzad et al. (2022), on the other hand, discussed digital twin applications with the titles of smart cities, design decision-making, product manufacturing, real-time progress monitoring, and facility management. A variety of data-related, high-fidelity modeling, and simulation technologies are needed for the implementation of DT (Opoku et al., 2021). When the literature dealing with the digital twin applications is examined, big data, artificial intelligence (AI), internet of things (IoT), augmented reality (AR), virtual reality (VR), and blockchain technologies are seen as supporting and are adapted for processing, storing and responding to the high-volume data obtained (Coupry et al., 2021; Y. Jiang, 2021; Pour Rahimian et al., 2020; Shahzad et al., 2022; Yitmen et al., 2021; J. Zhang

et al., 2021). Big data is used to express a data set with a huge size and volume that traditional data management tools and processing software remain insufficient. It is a collection of data, not a technology. Big data, which can be collected especially from new sources, can also be defined as data that contains a larger variety, arriving in increasing volumes and with more velocity. In their literature review on digital twin applications, Opoku et al. (2021) mentioned blockchain and smart contracts, BIM, IoT, GIS, VR, and AI as digital twin technologies that will respond to industry problems along with big data technology related to data collection tools. However, GIS will not be discussed in this section, as energy simulations fall outside the scope of project and construction project management. Furthermore, Ozturk (2021) found artificial intelligence, building information modeling, internet of things, virtual reality, and machine learning (considered within the scope of artificial intelligence) technologies among the concepts related to the digital twin in her scientometric analysis research with the keyword digital twin within the scope of the AECO/FM industry.

2.1.4.1 Internet of Things (IoT)

The concept of IoT represents the network in which physical objects (mechanical or digital tools, living beings, objects, etc.) supported by sensors and by technologies such as software and data processing are connected and exchanged data via the internet or other connection types. Dilakshan et al. (2021) define IoT as a system of "Things" that connect to and communicate with one another through the Internet or a private network and specify "Things" as "smart devices" that are connected to a network and carry out most of their communication with little to no human involvement. IoT devices have seen a spectacular expansion in recent years with the industry's quick development, and they penetrated many industries (Liang et al., 2021). Through the use of radio frequency identification, the global positioning system, and other information-sensing devices, it is an intelligent sensing network that can share and communicate information in a secure and effective manner (Qian, 2021). C. Zhang et al. (2022) state that the structure of IoT technology consists of the following four parts:

1. Perception Layer: The primary purpose of the sensing layer is to gather physical events and data that take place in the real world, such as quantities, identity, and location.

2. Network Layer: Connection types like internet, mobile or wireless network, etc. serve as the foundation for the network layer.
3. Application Layer: The final interaction between things and people for analysis and decision-making is completed by the application layer, which also uses it to promote collaboration and sharing.
4. Public Technology: All IoT layers in terms of recognition and resolution, security, and network administration, are related to public technologies.

IoT in construction is used to connect physical and virtual assets by acquiring, analyzing, and processing real-time and multi-source data from the actual operations for automated monitoring and early warning (T. Han et al., 2022; Z. H. Han et al., 2020). Additionally, IoT can be used to link the gathered data with the model to create an information system, and BIM can act as a central database (Zhansheng Liu et al., 2020; Qian, 2021). With the integration of BIM, it can accomplish real-time monitoring, positioning, data analysis, and surveillance of the site, such as equipment, material, climate, etc. monitoring, and improve quality and efficiency in terms of inventory management (Z. H. Han et al., 2020; Qian, 2021; Yu et al., 2019). Oke et al. (2020) in their research in which they compiled the application areas of IoT technology in the construction industry, revealed that the performance of safety, comfort, efficiency, revenue generation, energy consumption, transportation, health monitoring, security, privacy, communication, decision making, time and cost, pollution and waste, data management, efficiency, and productivity concepts was positively affected.

2.1.4.2 Artificial Intelligence (AI)

One of the key technologies in the world for Industrial Revolution 4.0 (Nguyen, 2021), artificial intelligence is the ability of a computer or computer-controlled robot to perform and simulate the processes or tasks that human intelligence is related to. The primary anticipated advantage of AI is that it will lighten the workload on time-taking tasks that a human to think, calculate, and control. The phrase artificial intelligence, which has roots in the 1940s but is still one of the most puzzling areas of computer science today, was first used by John McCarthy at a conference on the subject in 1956. AI is a term used to refer to artificial creations, such a knowledge that can learn, reason, plan, perceive, or process particular languages (Alheeti & Aldaiyat, 2021). The

ability to analyze multiple examples and produce machine learning models based on inputs and expected outputs is something provided to machines by humans (Hooda et al., 2021). A system that can learn from data is what is meant by the term "machine-learning," which refers to a subdivision and technology developed in the field of artificial intelligence (Nguyen, 2021). In addition to machine learning, there are technologies and disciplines such as Deep Learning, Pattern Recognition, Fuzzy Logic, Swarm Optimization, Decision Trees, and Evolutionary Computation under the umbrella of artificial intelligence, and all of them can find their applications in the construction industry (Hooda et al., 2021). Hooda stated that artificial intelligence applications have increased with technological developments and stated the three dimensions of artificial intelligence as follows: (1) the first dimension consists of the techniques and processes needed to teach machines to comprehend and carry out the proper actions in the same way as humans do; (2) based on a specific pattern recognition, the second dimension is all about the sensory and cognitive capacities of the robots, such as image processing; (3) the third dimension is the development of novel technology that can take the place of human labor. Automation technologies have become inevitable for the construction industry, which has started to digitalize in search of a solution to the problems it faces (Oliveira et al., 2021). Goh (2006) suggested 16 years ago that while organizations must acquire the fundamental building blocks of intelligent enterprise architecture, also industry professionals must adapt their ways of thinking to include artificial intelligence in their commercial and operational decisions. The author also noted that it may have uses in the areas of resource planning, cash flow and productivity estimation, optimization of site operations, and site equipment selection. Artificial intelligence is used in research, design, and intelligent computing to optimize and model complex structures that require high computing resources and can offer great alternatives for effective problem solving (Cao et al., 2021). Hooda et al. (2021) have compiled the most significant applications of AI in the construction industry: (1) decision-making using the parameters of project characteristics, risk, environment and organization, location, and workers with artificial neural network (ANN); (2) project plan adherence through the project life-cycle with the help of robotics and machine learning; (3) structural health monitoring; and with the IoT integration, (4 and 5) real-time monitoring and developing a smart city. In addition, the construction project management literature contains research showing that artificial intelligence improves decision-making,

productivity, efficiency, scheduling, cost, quality and safety performances (Alheeti & Aldaiyat, 2021; Aziz et al., 2014; Cao et al., 2021; Du, 2021; Nguyen, 2021; Oliveira et al., 2021; H. Wang & Hu, 2022a).

2.1.4.3 Virtual Reality (VR)

Virtual reality, a technology that has permeated even daily life, enables users to interact with artificially created and simulated virtual environments. It was created as a research result of a flight simulation in the 1960s (Ghanem, 2022). Y. Wang (2021) defined VR as a technology developed by the integration of computer graphics, multimedia, AI, simulation, and other related disciplines. Users can experience vision, hearing, and even smell in the virtual environment with realistic sceneries and objects offering an immersive experience (Xu, 2021). In today's technology, multi-screen digital rooms or wearable VR headsets called 'head mount display' can deliver this experimental environment. As can be understood from the previous definitions, VR acts as a visualization technology. VR initially gained popularity in the gaming and entertainment industries, but it didn't take long for it to reach the AECO/FM industry once it was realized that VR applications improved scenario visualization and simulation. Also, Shojaei et al. (2021) stated that advanced visual capabilities are essential for construction industry professionals and added that augmented reality (AR) and mixed reality (MR) were integrated into the industry along with VR. The author also noted that in general, VR applications are most commonly used in design education, building visualization, training operational tasks, structural analysis training, and safety training. Users of VR have the option to visually stroll through a 3D model of a future building (Ozcan-Deniz, 2022). BIM facilitates VR by providing the advanced model needed for such applications. It enables a more seamless and organic integration of VR (Ghanem, 2022). The combination of VR and BIM technologies improves the effect of virtual performance by simulating real building information through a digital information model, which has significant project management implications (Y. Wang, 2021; Xu, 2021). On basis, because of its 3D virtual environment, VR technology gives users the chance to interact with the building and production process and broaden the cognitive toolkits of professionals (Y. Wang, 2021). VR has benefited numerous project management domains, including communication and collaboration, security, logistics, control, and training, as a result

of these visualization possibilities (Dallasega et al., 2020; Ghanem, 2022; Ozcan-Deniz, 2022; Zhong & Hao, 2014).

2.1.4.4 Augmented Reality (AR)

AR refers to an enhanced version of the real physical world through technologies that bring computer-generated objects such as visual elements and sounds, into the user's physical environment. Machado & Vilela (2020) define AR as the combination of a real environment with computer-derived information. While similar smart technologies like wearable headsets are utilized to complement users' experiences, augmented reality differs from virtual reality in that it overlays virtual data on top of the real and physical world. It makes augmented reality more valuable in AECO/FM industry (M. J. Kim et al., 2011). It is because by incorporating images, audio, tactile feedback, and scent into the natural environment without altering its source, augmented reality is far closer to the real world compared to VR (Kivrak et al., 2013). The rapidly increasing use of AR has spread to different industries and has been used in many applications such as navigation, medicine, smart shopping, entertainment, education, production, museums and libraries, security, etc. (Karji et al., 2017). Indicating that the AECO/FM industry is one of the suitable areas for the application of augmented reality, Rohani et al. (2014) pointed out that the augmented reality environment, which can represent the realistic view for simulation, can display a combination of views of a real-world site and a computer-aided design model of a construction process, offering a potent way to generate project activities and resources. In essence, AR is used as a powerful visualization tool that enhances understanding by providing detailed visualization of plans or any element in the construction industry. It is important to provide efficient monitoring methods along with providing useful data to project managers in the construction industry (Ratajczak et al., 2019). By enhancing the visualization and giving stakeholders access to more intelligible 3D project data, the construction project management system is made more effective and simple (Bhadaniya et al., 2021; M. J. Kim et al., 2011; Zhong & Hao, 2014). Thus, it finds applications from the design to the maintenance phase of the building in many areas such as prevention of potential conflicts, clash detection, synergic site visualisation, construction project management training, and safety training (Chung et al., 2021; Karji et al., 2017; J. Kim & Irizarry, 2021; Rankohi & Waugh, 2013b; Rohani et al., 2014; Sepasgozar, 2020; Tayeh & Issa, 2020; Wen et al., 2021).

2.1.4.5 Smart Contracts and Blockchain

The concept of blockchain, which has become widespread with crypto coins such as bitcoin and ethereum, is known as their technical background. As a well-known example of Distributed Ledger Technology (DLT), blockchain technology enables storing and execution of programs using a tamper-proof and easily verifiable transactional ledger system (Sigalov et al., 2021). A network of nodes rather than a single one regulates communication between nodes in this secure distributed file system (Darabseh & Martins, 2020). A smart contract is a computer program that, under specific circumstances, executes the terms of a contract exactly as they are coded between the parties. Smart contracts are if/then pieces of computer code, which means they are coded to execute the next step of a task automatically when the previous is completed or certain conditions are met (J. Li & Kassem, 2021; Lin et al., 2021; Owusu et al., 2020). To maintain track of the relevant information for each user within the network, smart contracts are linked to a blockchain. Singh et al. (2021) identified four attributes for blockchain as decentralization, persistency, anonymity, and auditability, while Lin et al. (2021) identified six for especially construction projects: (1) openness; (2) anonymity; (3) safety and reliability; (4) immutability; (5) traceability, and (6) automated information processing. As a result of a decentralized chain that makes it simple to trace changes, hard to cheat or hack the data, and feasible to swiftly accomplish collaboration, blockchain users no longer have to rely on a centralized system for their exchanges and transactions (Wahab et al., 2022). Because they are only limited by the coding skills of the creator of the smart contract and the integrated technologies (i.e. BIM, IoT) on which they rely, smart contracts do away with the requirement for third parties like banks (J. Li & Kassem, 2021). So they warrant more trust than any centralised third-party alternative. Blockchain and smart contract technologies, as mentioned earlier, can be integrated with BIM, IoT, or data gathering tools like RFID (Darabseh & Martins, 2020). Thus the digital twin concept benefits from the use of blockchain technology since it makes data and communication more transparent and secure (Ni et al., 2021). Information, payments, procurement, supply chain, rules and compliance, contracts and delivery, disputes, and technological systems were recorded as the AECO/FM industry applications of blockchain and smart contracts by Li & Kassem (2021) after reviewing 153 sources of literature.

2.2 Digital Twin Practices on BIM Uses at Construction

A construction project's life cycle is made up of a series of tasks that must be finished to achieve the project's goals and objectives. Rankohi & Waugh (2013) stated the project phase dimensions in which they examined the literature as (1) initiation, (2) design development, (3) contract and pre-construction, (4) construction, and (5) maintenance. Schiavi et al. (2022) on the other hand, divided the lifecycle phases into three as design, construction, and post-construction. A committed team visualizes and collaborates on the project while doing defect management to find solutions prior to the start of construction. During the design phase, a building is conceptualized in three dimensions (Zaker & Coloma, 2018). Simulations of the building's structural soundness, lighting conditions, and potential weather effects are also part of this phase. The post-construction phase, which lasts for around 30 years, is the one with the longest duration in a building's life cycle (Schiavi et al., 2022). The activities of this phase include maintenance procedures that are carried out to offer an appropriate living and working space as well as to sustain equipment to prevent breakdowns. As the second and most complicated phase, construction involves both workers on the job site and those who work in engineering and design offices (Schiavi et al., 2022). A dynamic construction site is vulnerable to numerous risks that could jeopardize the project's timeline, the quality of the building, and the safety of workers (K. Kim et al., 2017). The project's life cycle can last anywhere from a few months and a few years. No matter how long a project's life cycle is, the project management process needs to be organized. Leading management techniques with experimental and technological tools must be used in the planning, coordination, control, and other procedures to meet the goal of management (Xie & Yang, 2021). The procedures of the organization, planning, leadership, coordination, scheduling, and control are typically used to carry out management. The project management requirements define the management structure, organizational responsibilities, position of roles, and scope of work, among other things. According to Ozturk (2021), in her scientific analysis, the terms "digital twin" and "lifecycle" have the greatest impact on research since, over time, the AECO/FM industry has turned its attention to digital twin research as a method for product lifecycle management.

Opoku et al. (2021), in their study investigating the applications of the digital twin in the construction industry, determined the lifecycle phases as the classification criteria.

In the industry, they observed that the research progressed more slowly until 2018 and increased in 2019, and they found a total of 22 case studies and application studies. Authors found that until 2022, the design and engineering phase has 11 application and case study research, the construction has 3, the operation and maintenance phase has 8, and the demolition phase has no application research as shown in Figure 2.7. Also, the fact that "architectural design" had the third-highest number of ties with “digital twin” in the scientific investigation suggests that the AECO/FM industry's digital transformation began with the architectural design process before moving on to other processes sequentially (Ozturk, 2021). Shahzad et al. (2022) also evaluated the reflection of the digital twin in the design phase as a 3D intelligent data model and revealed that the studies in this phase are much more advanced than the other phases. There is a lack of research on the digital twin technology for construction site management and its extensive applicability for construction sites, even though studies on the design phase or the transition from BIM to the digital twin are covered in the literature (J. Zhang et al., 2021). The author also highlighted a research (Boje et al., 2020) as one of the few studies under construction in the building industry, showing some potential methods and technologies for digital twins to be considered. Articles examining the status of the digital twin concept in the industry have revealed that construction needs further investigation (Opoku et al., 2021; Ozturk, 2021; Shahzad et al., 2022; J. Zhang et al., 2021).

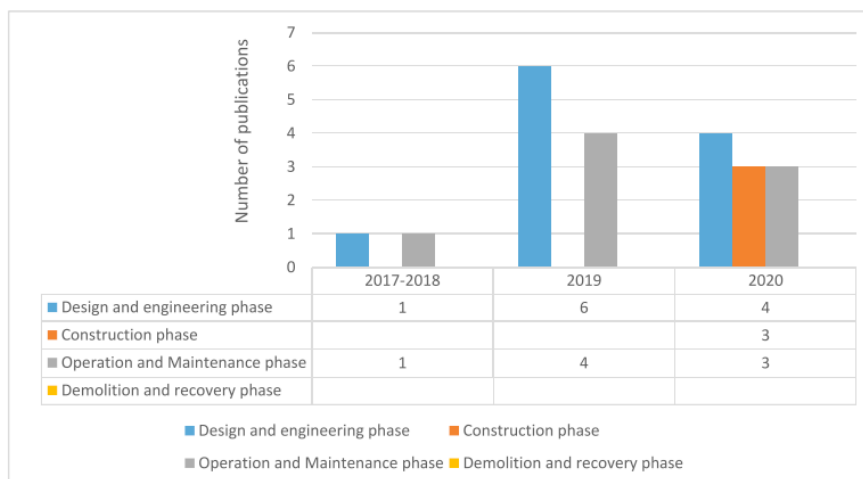


Figure 2.7 : Lifecycle phases of digital twin objects (Opoku et al., 2021)

The smart construction site is evolving quickly in the age of digitization thanks to the implementation of numerous digital tools, including cyper-physical systems, BIM,

laser scanning, sensing, RFID, web technology, and more (F. Jiang et al., 2021). BIM is regarded as a crucial source of data in all studies pertaining to smart cities or the AECO/FM industry. BIM is viewed as the digital twin's starting point since it serves as a 3D reference model with a wealth of semantic information that may be used in a variety of digital twin applications (Boje et al., 2020). BIM can be used in the construction industry as well as with sensors and other real-world and physical world linkages which is necessary for real-time monitoring and management. By analyzing the literature, Boje et al. (2020) compiled the use of bim in construction applications such as logistics, clash detection, site monitoring, quality control, safety management, simulation, visual communication, scheduling, and cost estimating. Although the use of BIM in construction is on the rise with increasing opportunities, the development of BIM to be a digital twin is not yet at a sufficient level, and it has been revealed in the literature that new areas of use can arise or existing areas can be improved in this way. A total of ten digital twin services have been identified that have the potential to further develop BIM and address enhanced construction management as will be discussed in the next titles.

2.2.1 Site Progress Monitoring

Monitoring the construction site is crucial during construction (Keyvanfar & Shafaghat, 2022). BIM use cases in site progress monitoring are based on a variety of new methods and technologies to monitor the site using photogrammetry and laser scanning on handheld mobile devices and aerial drones to capture site data and automate the BIM model during construction (Boje et al., 2020). By comparing as-planned 3D models and as-built photographs or other data types. F. Jiang et al. (2021) noted that visualization and computer vision techniques are used in an object-oriented manner to monitor building progress in detail. After several processing and acquisition processes, the data obtained from these technologies are reflected in the BIM model. This mirroring takes place with the effort of the responsible architect or engineers in the form of regular updates. Some studies revealing this process in the literature have addressed the difficulties of making sense of the huge amount of data that is planned to be transferred from the site to the digital model (Akanmu & Anumba, 2015). Validation of senseful data and interpretation of it to output real-time correct answers also remain challenges of the current BIM process (Boje et al., 2020). To improve the synchronization between virtual models in both directions, a digital twin strategy can

be used (Darabseh & Martins, 2020; F. Jiang et al., 2021). This is because, as discussed in previous chapters, digital twin technologies provide continuous and real-time data flow from the site to the model by automating the site monitoring process without requiring the human need to process data which is both challenging and time-consuming (Z. H. Han et al., 2020; Hooda et al., 2021; J. Li et al., 2019). And facilitate their visualization and understanding (Karji et al., 2017; J. Kim & Irizarry, 2021; Pour Rahimian et al., 2020). To enhance the tracking of changes and model updates, data sharing between the designers and the site, and real-time recording of the status of as-built parts (Akanmu & Anumba, 2015; Chengyi Zhang & Arditi, 2020).

2.2.2 Resource Allocation (labor, equipment, material) and Waste Management

The storage, usage, handling, disposal, waste collection, and other operations that take place on site after the delivery of products are included in site material management (Z. H. Han et al., 2020). As an integrated process, implementing a comprehensive resource management plan aids in achieving more predictable project results, cutting costs, raising productivity and quality, and creating a safer working environment (Z. H. Han et al., 2020; Liang et al., 2021). Cinquepalmi explained how the resource management process takes place in the BIM method. On predetermined and periodic dates during the construction, quality and quantity measurements are performed on the construction site, and the data collected is reported in the information model for each element under control. The measurements are made collaboratively by the experts in a geo-referenced and documented manner, and information like quantity, quality, time, cost, health, and safety are produced by measurements. The authors also emphasized that in the BIM methodology, these measurement processes should occur automatically. In this context, studies in the literature aim to improve situational monitoring of on-site construction resources, the identification, and elimination of waste and the identification of workflow disruptions, better planning and enhancing productivity based on visualization by integrating the BIM model with digital twin technologies such as IoT (Reinbold et al., 2019). With the digital twin sensors and mobile technologies, any desired resource such as workers, materials, and machinery in the construction site can be monitored on the virtual model. It provides the opportunity to make instant interventions by displaying the instant and real situations of the resources in the dynamic construction site environment instead of the planned locations. It is possible to collect real-time data regarding the location of resources in

the construction site, the movement of workers and materials during production, and the total time a worker spent in a certain location or inventory level (Z. H. Han et al., 2020; F. Jiang et al., 2021; Oke et al., 2020; Qian, 2021; Smaoui et al., 2018). As a result, by tying the data to the planning information, it will be easy to see whether the personnel and materials are where they need to be for their next assignment and identify any deviations quicker than when using status update data generated once a week or at the end of the day (Liang et al., 2021; Reinbold et al., 2019).

2.2.3 Clash Detection

Schedule conflict, resources and cost conflict, and construction site conflict are the three sub-uses that clash detection differentiates between (J. P. Zhang & Hu, 2010). 4D and 5D bim applications emerge as as-designed models at the stage of construction to avoid these clashes and overcome ineffective coordination and communication (Ammar et al., 2022; Bhadaniya et al., 2021; Isikdag, 2015; Zhen Liu et al., 2015). By processing different types of data, such as point clouds, digital or thermal images, and sensor data from laser scanners, cameras, and other devices, the digital twin, which focuses on geometric information, offers a visual and effective way for inspection (Bohn & Teizer, 2010; F. Jiang et al., 2021). Automated sensing with digital twin avoids the question marks about the model's completion, validity, and human factor of BIM adoption for clash management. It enriches the BIM model by reflecting the instant situation (as-is) and allows professionals to make alternative (what-if) planning simulations including construction tasks, temporary logistical operations, or plans for equipment distribution and provides an opportunity to examine the interaction of temporary construction sites and objects with existing and newly built areas (Boje et al., 2020). The second-most frequently mentioned activity in publications pertaining to construction is design review, which deals with finding conflicts between structural installations and architecture inside a virtual building model (Schiavi et al., 2022). Digital twin visualization technologies such as VR and AR work separately or together under the concept of mixed reality, providing the opportunity to observe collision detections in hard-to-reach areas with the help of simulation or hologram technologies, even from the office (Rohani et al., 2014; Tayeh & Issa, 2020; Zaker & Coloma, 2018). Thus, cooperation and communication between stakeholders are also improved.

2.2.4 Communication, Collaboration, and Decision Making

A crucial component of team communication and decision-making in the construction industry is visualization (Boje et al., 2020). The BIM solution has revolutionized communication between parties and decision-making processes (Goyal et al., 2020; Torrecilla-García et al., 2021; Xu, 2021). However, unlike the as-design model provided by BIM, the "real-time virtual model" provided by multiple digital twin sources and technologies with instantaneous, cross-checking, and cross-referencing data avoids the difficult manual processes caused by huge amounts of data obtained from the construction site. That is, in the digital twin, the data is more transparent, so it will be shared more freely, increasing cooperation and trust between the parties (J. Li et al., 2019). Bohn & Teizer (2010) noted that throughout the construction of a building project, the monitoring and control technologies discussed earlier in the thesis can assist project participants in making better decisions more quickly. With AI-supported decision-making, instant data can be processed according to the relevant user and all kinds of data can be understood (Vivi et al., 2019). The fact that the instant situation in the field can be monitored directly, with examples such as simulating a tour at the construction site with the help of advanced visualization tools, provides more valuable information to stakeholders and decision-making processes (Boje et al., 2020; Ozcan-Deniz, 2022; Rankohi & Waugh, 2013a; Rohani et al., 2014; Tayeh & Issa, 2020). Additionally, with the help of various technological advancements, current BIM uses will become easier to compare construction simulations with real-time site updates (Boje et al., 2020; Xu, 2021).

2.2.5 Scheduling and Cost Management

When creating a 4D model, the phases of construction must be broken down into a setting where people, materials, equipment, and spaces are linked to the intended activities. This makes it simpler to verify construction sequences, manage variations, and compare various scenarios side by side (Agostinelli, Ruperto, et al., 2019). And the 5D model, which is coupled with the 3D model to view the relevant expenses through time, offers techniques for extracting and analyzing costs, more predictable estimations, quantities, materials, equipment, and labor (Agostinelli, Cinquepalmi, et al., 2019). Time planning is essential and has a significant impact on cost planning since it grows in direct proportion to the potential for delays. To improve 4D and 5D

dimensions to utilize resources correctly and to keep costs at an estimated level, digital twin reduces the workload on tasks that require time for a human and inform the managers about the errors and their causes at the right time to improve the management at the construction instant changes of construction site dynamics like over-employment or too long production time (Boje et al., 2020). As an example, Aziz et al. (2014) developed an intelligent optimization model with the help of artificial intelligence. They provided optimized resource allocation to decrease project duration by supporting the famous scheduling tool Critical Path Method, with artificial intelligence algorithms. Researchers trying to develop the 4D model were able to easily identify bottlenecks causing delays and forecast the number of building tasks that would be needed in the future (Pan & Zhang, 2021). Additionally, they were able to quickly examine various design possibilities on models and enhance Key Performance Indicators (KPIs) including overall construction time and cost thanks to digital twin visualization tools (Dallasega et al., 2020; Ghanem, 2022). Bohn & Teizer (2010), on the other hand, were able to compare as-built data with planned calendars with automated cameras. Near-future schedules can be predicted by optimizing the planned and actual schedule data during the construction with the help of artificial intelligence, daily resource consumption can be formulated to prevent short-term peaks and troughs, and the statistical workload on humans can be reduced in general (Hu et al., 2019; H. Wang & Hu, 2022a; Yin, 2021). Digital twin uncovers and analyzes costs and provides precise cost estimations and predictions using real-time data and machine learning algorithms like ANN (Cao et al., 2021; Nguyen, 2021). With the help of IoT, it labels, tracks, and monitors the desired elements to prevent negative cost effects like incorrect deliveries, misallocating funds, and theft (Oke et al., 2020). Up to 20% of building costs can be eliminated by using AI, IoT, and robotics (Alheeti & Aldaiyat, 2021).

2.2.6 Risk Management

Risks in the early stages of projects are reduced as a result of the practical application of BIM (Goyal et al., 2020). However, due to the rapid variables of the construction, it is also important to track the risks for a better construction project management (Alheeti & Aldaiyat, 2021). Planning, tracking, monitoring, and operating risks can be supported by the digital twin (J. Zhang et al., 2022). The previously mentioned digital twin's real-time virtual model avoids the effort and waste of time in processing

and response the measurements and controls carried out for the risk management plan (Arup, 2019). Nguyen (2021) stated that machine learning applications of construction project management can be a response to various risks, from conflicts between stakeholders, to project duration or cost. In the literature, studies using ANN, one of the machine learning types, have been used for applications such as assessing risk categories and values, risk assessment modeling with approximate sets to reduce uncertainties, and determining cost deviations deriving from potential hazards to reveal potential risks and turn them into actionable notifications for managers (Cao et al., 2021). According to the decided risk value, ANNs are also used to calculate the percentage difference between actual costs and projected floats at completion levels of 30, 50, 70, and 100%.

2.2.7 Logistics and Supply-Chain

According to Y. Li & Liu (2019), logistics deals with the movement of supplies and equipment from their point of origin to the workplace, and the majority of the gross work done in construction entails purchasing goods and services from suppliers and subcontractors. Improving the management of the logistics network requires an inclusive supply chain, in which tasks such as the delivery of materials and equipment connected with their prerequisites (Boje et al., 2020). Opoku et al. (2021) stated that one of the 6 key applications they found in their study, in which they defined the basic applications of the digital twin application in the construction industry at various lifecycle stages, is logistics processes. Digital twin enhances the as-designed model and enables pro-active modeling, eliminates the lack of integration of on-site and off-site supply chain actors, monitors layouts of the construction site, updates the real-time location of the resources, enables the tracking of an ordered material from the factory to the construction site, and give professionals an optimized duration and sequence recommendations (Boje et al., 2020). These smart logistics processes directly reduce costs (Greif et al., 2020). Drones, cameras, and sensors have been used to move materials on construction sites and deliver goods from suppliers, which will help supply chain managers to overcome logistical difficulties in the construction industry (Bohn & Teizer, 2010; Y. Li & Liu, 2019; Oke et al., 2020; Patel et al., 2021; Ruperto & Strappini, 2021). For instance, real-time location systems like GPS, ultra-wideband radio, or radio frequency identification were utilized to detect, identify, and track the whereabouts of materials that were marked (Y. Li & Liu, 2019).

2.2.8 Safety Detection

With the visualization technologies evolution, BIM has found applications to solve construction safety issues, including risk recognition and prevention, as well as workers' safety training (Torrecilla-García et al., 2021). Additionally, it can simulate the construction process and its connections, detect potential safety risks on the site, review the construction plan through in-depth simulation, comprehend the risky conditions on the site, and take preventive action (B. Zhang, 2021). But, the implementation process of the safety management workflow is insufficient due to the existing data acquisition from the construction site, lack of safety analysis information, and their processing methods (J. P. Zhang & Hu, 2010). In addition, subcontracting concepts and temporary workers cause the use of BIM to be neglected or continuous data changes (Boje et al., 2020). A smart construction site framework can be developed for safety management based on the digital twin concept, allowing personnel, mechanical, and other site risks to generate warnings and be controlled (F. Jiang et al., 2021). Sensors, drones, and cameras gather data on the workers' presence on the job site, verify that they are following safety regulations like wearing helmets, and look for signs of immobility or falling with the help of artificial intelligence (Alheeti & Aldaiyat, 2021; Assadzadeh et al., 2021; Oke et al., 2020; Yi & Qu, 2021). And regular site surveillance can be conducted cheaper and easier (Costa et al., 2016). Virtual simulations of evacuation and field safety, AI-powered automated processes, and safety training with wearable devices can shed additional light on previously unforeseen near-term security threats and dangers and raise employee awareness (Baduge et al., 2022; K. Kim et al., 2017; Xu, 2021).



3. RESEARCH METHODOLOGY

Although the impact of studies on digital construction, especially for the design phase, is visible in the literature, there is a lack of research on digital twin technology for construction and its comprehensive applicability for construction sites. The aim of this study is to shed a light on the interaction of the digital twin and BIM from a construction project management perspective; to investigate the influences of the digital twin during the construction phase of the project lifecycle. The study attempts to find answers to three research questions: (1) “What are the characteristics and practices of the digital twin in the AECO industry?”; (2) “What are the functions and applications of the digital twin in the construction from a management perspective?”; (3) “To what extent and how can the digital twin support BIM in the construction?”. To provide an effective response to the objective, this thesis employs a two-step methodology: (1) a comprehensive synthesis of the literature on the digital twin through the lens of construction project management and (2) a questionnaire survey. In the first step, the extant literature on the digital twin and BIM is investigated, and then their applications in construction are identified and compared. In the second step, a questionnaire survey was conducted to measure the influence of digital twin services in the construction project management literature on parallel BIM uses with the aim of understanding the importance of these services for professionals. Figure 3.1 represents the flow and stages of the research methodology. To perform a detailed background analysis, the Scopus database was selected for data extraction and a comprehensive literature review was conducted to find out the digital twin characteristics, practices, their relationship with BIM and finally functions and applications of both in the construction. The reason for choosing Scopus is that it has a larger scope and provides access to more recent publications (Opoku et al., 2021). After synthesizing the digital twin literature, Title-Abstract-Keywords filtering in Scopus' advanced search engine was used in 2 separate parts. The first and changing part was digital twin practices such as "artificial intelligence OR ai" and "internet of things OR iot", while the second and unchanged part was "construction management" for each search run. The articles

included in the search results that were not related to the construction industry were eliminated.

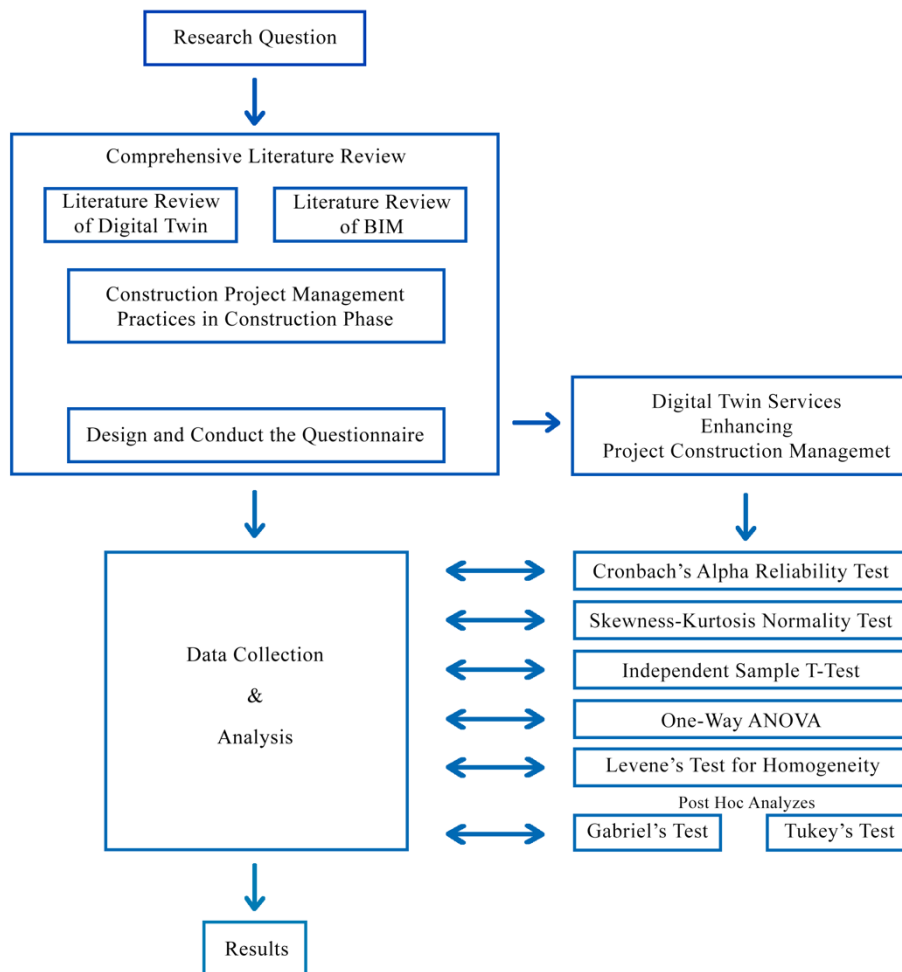


Figure 3.1 : Flow and stages of the research methodology

The literature review, based on eye-opening articles from leading journals, provided a basis for further research and uncovered the knowledge gap. As noted in section 2.2, many authors in the digital twin literature have highlighted that the building lifecycle needs further work during the construction (Opoku et al., 2021; Ozturk, 2021; Shahzad et al., 2022; J. Zhang et al., 2021). Having identified this knowledge gap, related resources and applications of the digital twin during construction were discussed and digital twin services which address enhanced construction project management with the potential for the further improvement of BIM were compiled in the literature. These are site progress monitoring, resource allocation and waste management, clash detection, decision making, communication and collaboration, cost management, scheduling, risk management, logistics and supply chain, and safety detection as

shown in Table 3.1. An attempt was then made to measure the influence of the digital twin concept on BIM uses during construction in the context of construction management to understand the importance of these services compiled from the literature for professionals.

Table 3.1 : Digital twin services during construction

Digital Twin Services	References
“Site Progress Monitoring”	(Akanmu & Anumba, 2015; Boje et al., 2020; Darabsch & Martins, 2020; Z. H. Han et al., 2020; Hooda et al., 2021; F. Jiang et al., 2021; Karji et al., 2017; J. Kim & Irizarry, 2021; J. Li et al., 2019; Pour Rahimian et al., 2020; Chengyi Zhang & Arditi, 2020)
“Resource Allocation and Waste Management”	(Z. H. Han et al., 2020; F. Jiang et al., 2021; Liang et al., 2021; Oke et al., 2020; Qian, 2021; Reinbold et al., 2019; Smaoui et al., 2018)
“Clash Detection”	(Bohn & Teizer, 2010; Boje et al., 2020; F. Jiang et al., 2021; Y. Jiang, 2021; Rohani et al., 2014; Schiavi et al., 2022; Tayeh & Issa, 2020; Zaker & Coloma, 2018)
“Decision Making” and “Communication and Collaboration”	(Bohn & Teizer, 2010; Boje et al., 2020; J. Li et al., 2019; Ozcan-Deniz, 2022; Rankohi & Waugh, 2013b; Rohani et al., 2014; Tayeh & Issa, 2020; Vivi et al., 2019; Xu, 2021)
“Cost Management” and “Scheduling”	(Alheeti & Aldaiyat, 2021; Aziz et al., 2014; Bohn & Teizer, 2010; Boje et al., 2020; Cao et al., 2021; Dallasega et al., 2020; Ghanem, 2022; Hu et al., 2019; Nguyen, 2021; Oke et al., 2020; Pan & Zhang, 2021; H. Wang & Hu, 2022b; Yin, 2021)
“Risk Management”	(Alheeti & Aldaiyat, 2021; Cao et al., 2021; Arup, 2019; Goyal et al., 2020; Nguyen, 2021; J. Zhang et al., 2022)
“Logistics and Supply-Chain”	(Bohn & Teizer, 2010; Boje et al., 2020; Greif et al., 2020; Y. Li & Liu, 2019; Oke et al., 2020; Opoku et al., 2021; Patel et al., 2021; Ruperto & Strappini, 2021)
“Safety Detection”	(Alheeti & Aldaiyat, 2021; Assadzadeh et al., 2021; Baduge et al., 2022; Boje et al., 2020; Costa et al., 2016; F. Jiang et al., 2021; K. Kim et al., 2017; Oke et al., 2020; Xu, 2021; Yi & Qu, 2021)

A questionnaire was designed by adapting the above literature outputs. In the two-part questionnaire, the first part captures general information about the respondents and the second part gathers information about the influence of Digital Twin services on BIM

uses on a 5-point Likert scale with 1 = not effective, 2 = slightly effective, 3 = moderately effective, 4 = very effective, and 5 = extremely effective. Google Forms, a web-based survey package, was used to collect information from respondents because of its simplicity and flexibility. Questions regarding both the demographic details of respondents and the influence level of digital twin services are provided in Appendix A. The questionnaire targeted industry experts who have experience with the digital twin and/or BIM. Purposive sampling was used as the sampling methodology. 108 industry experts were reached through the LinkedIn platform and 70 responses were collected. The response rate of the questionnaire turned out to be 65%. All responses were evaluated in the study, as all collected responses remained valid. The data obtained were analysed using Statistical Package for Social Sciences, SPSS v.27 software.

A series of sequential statistical tests were planned to analyze the perceptions of experts and search for any statistically significant difference between them. Firstly, the reliability of the data was tested with Cronbach's alpha reliability test. Then, the Skewness-Kurtosis normality distribution test was performed to decide which statistical tests can be applied to the obtained data. After it was revealed that the data were normally distributed, Pearson's correlation test was applied to see if there is a linear relationship between variables. Further analysis was conducted by performing independent-samples t-tests for comparing experts' opinions. One-way ANOVA test was another analysis that was applied to see the different perceptions. Finally, to uncover statistically significant differences between groups, appropriate post-hoc tests were applied. Levene's test was applied to measure the homogeneity of variances before post-hoc analyses. Accordingly, for variables which have non-homogeneously distributed variances, the Games-Howell test was applied. Additionally, the Gabriel's t and the Tukey tests were applied to the variables which have homogeneously distributed variances.

4. DATA ANALYSIS AND RESULTS

In line with the aim of the study, the 2-part questionnaire was sent to both private industry employees and academics who are BIM experts. All 70 responses obtained in total were evaluated in the study as they were valid for further analysis. Before starting the statistical analysis, Cronbach's alpha reliability test was conducted to test the reliability of the collected responses. The Cronbach's alpha (α) value of the study obtained from the responses turned out to be a very acceptable value of 0.893. According to Taber (2018), 0.7 was stated as a valid value for reliability, while the closer the value to 1, the better the reliability level. After testing the reliability of the study, further statistical analyzes were performed. The findings of the study are presented in two parts. The first part includes general information about the survey participants. Participants' perceptions about the digital twin influences are given in the second part by presenting statistical analysis results.

4.1 Participations' Demographics

70 experts participated in the questionnaire survey conducted by Google Forms. 41 per cent of the participants are architects, 30 per cent are civil engineers, and the remaining 29 per cent define themselves as mechanical engineers, software engineers, geomatics engineers, project managers and construction technicians. In the question asked about the education level of the participants, it was revealed that 20 of them have a bachelor's degree, 10 of them are studying for a master, 17 of them have a master's degree, 7 of them are studying for a doctorate and 16 of them are holding a PhD. The distribution of the participants according to their industry experience was realized as 20, 17, 22, 14 and 27 per cent respectively, in five categories: less than 2 years, 3 - 5 years, 6 - 10 years, 11 - 15 years and 15+ years. 27% of the participants are associated with academy, 19% of them are acting as client/developer, 24% of them are working in a contractor company, and 30% of them are giving consultancy services . Also, the participants were divided equally (50-50) from Turkey and internationally. Countries that participated from abroad were Taiwan, Kenya, Israel, United Arab Emirates

(UAE), Ireland, United States of America (US), Azerbaijan, Russia, India, Algeria, Ethiopia, England, Kazakhstan, Vietnam, Germany, Nigeria, Canada, Hungary, South Africa, Sweden, Malaysia, India, Australia, and Bahrain. The roles undertaken by the participants were split as follows: 14 per cent BIM manager, 20 per cent BIM architect or engineer, 36 per cent senior manager, 14 per cent academic staff, and 16 per cent “other”. Other options include consultants, students, project control specialists and planning engineers. The proportion of participants who have tried any of the Digital Twin practices is 57 per cent. Finally, the distribution of participants according to their experience in BIM or Digital Twin is as follows: 13 per cent for less than a year, 23 per cent for 1-2 years, 19 per cent for 3-5 years, 24 per cent for 5 – 10 years, and 21 per cent for more than 10 years. Table 4.1 summarizes the characteristics of the survey participants.

Table 4.1 : Characteristics of the survey participants

Demographic Variable	Categories	Number of Responses (n)	Percentage of Responses (%)
Profession	Architecture	29	41%
	Civil Engineering	21	30%
	Other	20	29%
Educational Level	Bachelor	20	29%
	Studying Master	10	14%
	Master	17	24%
	Studying Doctorate	7	10%
	Doctorate	16	23%
Years of Industry Experience	< 2 Years	14	20%
	3 – 5 Years	12	17%
	6 – 10 Years	15	22%
	11 – 15 Years	10	14%
	> 15 Years	19	27%
Organization	Academic	19	27%
	Client / Developer	13	19%
	Contractor	17	24%
	Consultant	21	30%
Country	Turkey	35	50%
	International	35	50%

Table 4.1 (continued) : Characteristics of the survey participants

Demographic Variable	Categories	Number of Responses (n)	Percentage of Responses (%)
Role	BIM Manager	10	14%
	BIM Designer	14	20%
	Senior / Manager	25	36%
	Academic	10	14%
	Other	11	16%
Digital Twin User	Yes	40	57%
	No	30	43%
Years of BIM or DT Experience	< 1 Year	9	13%
	1 – 2 Years	16	23%
	3 – 5 Years	13	19%
	5 – 10 Years	17	24%
	> 10 Years	15	21%

4.2 Digital Twin Influence on Construction Project Management

To analyze the participants' perceptions of the digital twin influence on construction project management, several statistical analyses were performed. Since the reliability of the questionnaire is verified, the Skewness-Kurtosis normality distribution test was applied to determine whether the sample data were normally distributed. According to Tabachnick & Fidell (2013), Skewness-Kurtosis values should be between +1.5 and -1.5. The relevant values of the survey variables are given in Table 4.2. The values of the skewness-kurtosis test for all variables are between +1.5 and -1.5, so it can be said that the data of the study have a normal distribution. In this way, it has been shown that it is appropriate to use parametric tests in the further analysis of the study since they require a normally distributed sample population. Additionally, Table 4.2 presents the mean scores for the variables of the study.

Table 4.2 : Skewness-Kurtosis normality distribution of variables

Variables (Influence on..)	Mean	Std. Deviation	Skewness	Kurtosis
Communication and Collaboration	4.34	.796	-.704	-1.058
Clash Detection	4.27	.962	-1.280	1.137
Decision Making	4.23	.820	-.776	-.140
Scheduling	4.17	.963	-1.158	.964
Site Progress Monitoring	4.11	.843	-.670	-.184
Resource Alloc. & Waste Man.	4.09	.959	-.885	.360
Cost Management	4.01	1.028	-.770	-.194
Risk Management	3.99	.893	-.601	.283
Logistics and Supply-Chain	3.83	1.076	-.581	-.325
Safety Detection	3.83	1.076	-.796	.287

High mean scores show that participants attach great importance to given digital twin services. Communication and collaboration had a mean of 4.34, followed by clash detection with a mean of 4.27, and decision-making with a mean of 4.23. Conversely, the lowest mean score of 3.83 belongs to the logistics and supply chain and safety detection variables. From these results, it can be concluded that digital twin services implemented during construction have a significant influence on BIM as they go beyond their uses in the context of construction project management.

The Pearson bivariate correlation analysis was performed to examine the relationships between the variables within all the ten influences as listed in Table 4.3. The correlation has a value between -1 to 1, with a value of -1 meaning a total negative linear correlation, 0 being no correlation, and + 1 meaning a total positive correlation. Since project management is an inclusive process and each variable is one of the project management services that create positive effects on project outputs, it is not surprising that there is a significant positive correlation between almost all variables. As expected, most of the variables were found to be correlated in the range of 0.310 to 0.729 with a two-tailed correlation significant at 0.01 level. Only safety detection and site progress monitoring have correlations of 0.293 with a two-tailed correlation significant at 0.05 level. No significant correlation was found between decision-making and resource allocation and waste management variables, and risk management and clash detection variables. The correlations between all variables are shown in Table 4.3.

Table 4.3 : Correlations between digital twin service variables

Variables (Influence on..)		A	B	C	D	E	F	G	H	I	J
Site Progress Monitoring (A)	Pearson Correlation	1.000									
	Sig. (2-tailed)										
Resource Allocation and Waste Management (B)	Pearson Correlation	.310**	1.000								
	Sig. (2-tailed)	0.009									
Clash Detection (C)	Pearson Correlation	.336**	.430**	1.000							
	Sig. (2-tailed)	0.004	0.000								
Decision Making (D)	Pearson Correlation	.549**	0.233	.472**	1.000						
	Sig. (2-tailed)	0.000	0.052	0.000							
Communication and Collaboration (E)	Pearson Correlation	.502**	.359**	.501**	.633**	1.000					
	Sig. (2-tailed)	0.000	0.002	0.000	0.000						
Cost Management (F)	Pearson Correlation	.349**	.469**	.362**	.512**	.401**	1.000				
	Sig. (2-tailed)	0.003	0.000	0.002	0.000	0.001					
Scheduling (G)	Pearson Correlation	.440**	.470**	.481**	.537**	.527**	.729**	1.000			
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000				
Risk Management (H)	Pearson Correlation	.426**	.340**	0.190	.579**	.374**	.490**	.543**	1.000		
	Sig. (2-tailed)	0.000	0.004	0.115	0.000	0.001	0.000	0.000			
Logistics and Supply-Chain (I)	Pearson Correlation	.373**	.379**	.368**	.538**	.458**	.591**	.588**	.586**	1.000	
	Sig. (2-tailed)	0.001	0.001	0.002	0.000	0.000	0.000	0.000	0.000		
Safety Detection (J)	Pearson Correlation	.293*	.436**	.284*	.522**	.408**	.500**	.490**	.601**	.675**	1.000
	Sig. (2-tailed)	0.014	0.000	0.017	0.000	0.000	0.000	0.000	0.000	0.000	

** Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

For further analysis, independent-samples t-test and analyzes of variance (ANOVA) were performed to analyze the statistical significance of these influences rated by experts, their interactions with each other, and the effects of these interactions on the dependent variable. Two independent sample t-tests were conducted to examine whether the groupings divided into two perceived the influence of the services differently. The results of the tests, in which participants were grouped according to their status as users of the digital twin and whether they were from Turkey or abroad, are shown in Tables 4.4 and 4.5.

Table 4.4 : T-test results for the digital twin service variables by digital twin users and non-users.

Variables (Influence on..)	Groups	Mean	Std. Deviation	t	p- value																																																																														
Communication and Collaboration	DT User	4.47	.751	1.622	.110																																																																														
	Non-User	4.17	.834			Clash Detection	DT User	4.35	1.075	.787	.434	Non-User	4.17	.791	Decision Making	DT User	4.35	.736	1.443	.154	Non-User	4.07	.907	Scheduling	DT User	4.28	.905	1.040	.302	Non-User	4.03	1.033	Site Progress Monitoring	DT User	4.22	.733	1.274	.207	Non-User	3.97	.964	Resource Allocation & Waste Management	DT User	4.00	1.038	-.862	.392	Non-User	4.20	.847	Cost Management	DT User	4.18	.931	1.524	.132	Non-User	3.80	1.126	Risk Management	DT User	3.90	.928	-.927	.357	Non-User	4.10	.845	Logistics and Supply-Chain	DT User	3.75	1.056	-.703	.485	Non-User	3.93	1.112	Safety Detection	DT User	3.78	1.121	-.478	.634
Clash Detection	DT User	4.35	1.075	.787	.434																																																																														
	Non-User	4.17	.791			Decision Making	DT User	4.35	.736	1.443	.154	Non-User	4.07	.907	Scheduling	DT User	4.28	.905	1.040	.302	Non-User	4.03	1.033	Site Progress Monitoring	DT User	4.22	.733	1.274	.207	Non-User	3.97	.964	Resource Allocation & Waste Management	DT User	4.00	1.038	-.862	.392	Non-User	4.20	.847	Cost Management	DT User	4.18	.931	1.524	.132	Non-User	3.80	1.126	Risk Management	DT User	3.90	.928	-.927	.357	Non-User	4.10	.845	Logistics and Supply-Chain	DT User	3.75	1.056	-.703	.485	Non-User	3.93	1.112	Safety Detection	DT User	3.78	1.121	-.478	.634	Non-User	3.90	1.029						
Decision Making	DT User	4.35	.736	1.443	.154																																																																														
	Non-User	4.07	.907			Scheduling	DT User	4.28	.905	1.040	.302	Non-User	4.03	1.033	Site Progress Monitoring	DT User	4.22	.733	1.274	.207	Non-User	3.97	.964	Resource Allocation & Waste Management	DT User	4.00	1.038	-.862	.392	Non-User	4.20	.847	Cost Management	DT User	4.18	.931	1.524	.132	Non-User	3.80	1.126	Risk Management	DT User	3.90	.928	-.927	.357	Non-User	4.10	.845	Logistics and Supply-Chain	DT User	3.75	1.056	-.703	.485	Non-User	3.93	1.112	Safety Detection	DT User	3.78	1.121	-.478	.634	Non-User	3.90	1.029															
Scheduling	DT User	4.28	.905	1.040	.302																																																																														
	Non-User	4.03	1.033			Site Progress Monitoring	DT User	4.22	.733	1.274	.207	Non-User	3.97	.964	Resource Allocation & Waste Management	DT User	4.00	1.038	-.862	.392	Non-User	4.20	.847	Cost Management	DT User	4.18	.931	1.524	.132	Non-User	3.80	1.126	Risk Management	DT User	3.90	.928	-.927	.357	Non-User	4.10	.845	Logistics and Supply-Chain	DT User	3.75	1.056	-.703	.485	Non-User	3.93	1.112	Safety Detection	DT User	3.78	1.121	-.478	.634	Non-User	3.90	1.029																								
Site Progress Monitoring	DT User	4.22	.733	1.274	.207																																																																														
	Non-User	3.97	.964			Resource Allocation & Waste Management	DT User	4.00	1.038	-.862	.392	Non-User	4.20	.847	Cost Management	DT User	4.18	.931	1.524	.132	Non-User	3.80	1.126	Risk Management	DT User	3.90	.928	-.927	.357	Non-User	4.10	.845	Logistics and Supply-Chain	DT User	3.75	1.056	-.703	.485	Non-User	3.93	1.112	Safety Detection	DT User	3.78	1.121	-.478	.634	Non-User	3.90	1.029																																	
Resource Allocation & Waste Management	DT User	4.00	1.038	-.862	.392																																																																														
	Non-User	4.20	.847			Cost Management	DT User	4.18	.931	1.524	.132	Non-User	3.80	1.126	Risk Management	DT User	3.90	.928	-.927	.357	Non-User	4.10	.845	Logistics and Supply-Chain	DT User	3.75	1.056	-.703	.485	Non-User	3.93	1.112	Safety Detection	DT User	3.78	1.121	-.478	.634	Non-User	3.90	1.029																																										
Cost Management	DT User	4.18	.931	1.524	.132																																																																														
	Non-User	3.80	1.126			Risk Management	DT User	3.90	.928	-.927	.357	Non-User	4.10	.845	Logistics and Supply-Chain	DT User	3.75	1.056	-.703	.485	Non-User	3.93	1.112	Safety Detection	DT User	3.78	1.121	-.478	.634	Non-User	3.90	1.029																																																			
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	Non-User	4.10	.845			Logistics and Supply-Chain	DT User	3.75	1.056	-.703	.485	Non-User	3.93	1.112	Safety Detection	DT User	3.78	1.121	-.478	.634	Non-User	3.90	1.029																																																												
Logistics and Supply-Chain	DT User	3.75	1.056	-.703	.485																																																																														
	Non-User	3.93	1.112			Safety Detection	DT User	3.78	1.121	-.478	.634	Non-User	3.90	1.029																																																																					
Safety Detection	DT User	3.78	1.121	-.478	.634																																																																														
	Non-User	3.90	1.029																																																																																

When divided into groups based on affiliation with digital twin practice users, the numbers split into 40 and 30. 40 out of 70 participants gave a positive answer to the

question "Do you use any Digital Twin practice in your company?". To understand if there was a significant relationship between the groups in the responses collected, the confidence interval percentage was set at 95, and the independent-samples t-test was performed. Since all p-values were greater than 0.05, it was determined that views on the variables did not differ between digital twin users and non-users.

Table 4.5 : T-test results of the t-test for the digital twin service variables by domestic and international experts.

Variables (Influence on..)	Groups	Mean	Std. Deviation	t	p- value
Communication and Collaboration	Domestic	4.40	.695	.597	.552
	International	4.29	.893		
Clash Detection	Domestic	4.49	.818	1.899	.062
	International	4.06	1.056		
Decision Making	Domestic	4.37	.646	1.471	.147
	International	4.09	.951		
Scheduling	Domestic	4.40	.914	2.031	.046*
	International	3.94	.968		
Site Progress Monitoring	Domestic	4.14	.845	.282	.779
	International	4.09	.853		
Resource Allocation & Waste Management	Domestic	4.20	.833	.997	.322
	International	3.97	1.071		
Cost Management	Domestic	4.20	1.079	1.525	.132
	International	3.89	.954		
Risk Management	Domestic	4.14	.772	1.486	.142
	International	3.83	.985		
Logistics and Supply- Chain	Domestic	4.00	1.029	1.340	.185
	International	3.66	1.110		
Safety Detection	Domestic	4.00	1.138	1.340	.185
	International	3.66	.998		

* T-test result is significant at the 0.05 level (two-tailed). $p < 0.05$

As mentioned before, the division of the participants according to the countries in which they carry out their activities was made in exactly two equal parts. 35 participants are working in Turkey and the remaining 35 participants are working abroad in 24 different countries. In the independent-samples t-tests performed with this group of international and domestic experts, the confidence interval percentage

was again set to 95. No p-values below 0.05 were found for the digital twin services variables, except for scheduling. It was found that views on the other variables did not differ between domestic and international experts. The p-value of the scheduling variable was found to be 0.046. Although it can be said that views differ statistically between groups, it should be kept in mind that there is no significant difference between means, even if the p-value is less than 0.05. When rated, domestic experts had a mean of 4.40, while international experts had a mean of 3.94.

One-Way ANOVA tests were applied to the data that met the conditions such as reliability and normality to understand if a variable differs for more than two different groups. ANOVA is a set of statistical models used to analyze group means and the operations that depend on them. The first grouping for applying the ANOVA tests to the variables was done according to the organizational structures of the participants. Participants were grouped into 4 different categories, namely academics, clients/developers, contractors, and consultants. The results of the test are shown in Table 4.6 and rankings of mean scores depending on the results are given in Table 4.7.

Table 4.6 : ANOVA results for digital twin service variables by organizational structures

Variables	Groups	N	Mean	Std. Deviation	f	p-value
Communication and Collaboration	Academics	19	4.37	.831	1.383	.256
	Clients / Dev.	13	4.23	.832		
Clash Detection	Contractors	17	4.65	.606	.684	.565
	Consultants	21	4.14	.854		
Decision Making	Academics	19	4.37	.684	3.770	.015*
	Clients / Dev.	13	4.23	1.092		
	Contractors	17	4.47	.943		
	Consultants	21	4.05	1.117		
Decision Making	Academics	19	4.37	.761	3.770	.015*
	Clients / Dev.	13	3.77	1.092		
	Contractors	17	4.65	.493		
	Consultants	21	4.05	.740		

Table 4.6 (continued) : ANOVA results for digital twin service variables by organizational structures

Variables	Groups	N	Mean	Std. Deviation	f	p-value
Scheduling	Academics	19	4.26	.733	.363	.780
	Clients / Dev.	13	3.92	1.256		
	Contractors	17	4.24	1.033		
	Consultants	21	4.19	.928		
Site Progress Monitoring	Academics	19	4.16	.834	1.879	.142
	Clients / Dev.	13	3.69	1.109		
	Contractors	17	4.41	.618		
	Consultants	21	4.10	.768		
Resource Allocation and Waste Management	Academics	19	4.05	1.079	.195	.900
	Clients / Dev.	13	4.08	.862		
	Contractors	17	4.24	.903		
	Consultants	21	4.00	1.000		
Cost Management	Academics	19	4.16	.834	1.065	.370
	Clients / Dev.	13	3.62	1.261		
	Contractors	17	4.24	1.033		
	Consultants	21	3.95	1.024		
Risk Management	Academics	19	4.21	.787	3.462	.021*
	Clients / Dev.	13	3.46	1.198		
	Contractors	17	4.35	.786		
	Consultants	21	3.81	.680		
Logistics and Supply-Chain	Academics	19	4.11	.994	3.492	.020*
	Clients / Dev.	13	3.08	1.320		
	Contractors	17	4.18	.951		
	Consultants	21	3.76	.889		
Safety Detection	Academics	19	3.95	.911	1.519	.218
	Clients / Dev.	13	3.38	1.557		
	Contractors	17	4.18	1.074		
	Consultants	21	3.71	.784		

* ANOVA result is significant at the 0.05 level. $p < 0.05$

Table 4.7 : Rankings of the influence of the digital twin services by organizational structures.

Variables	All		Academics		Clients		Contractors		Consultants	
	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank
Communication and Collaboration	4.34	1	4.37	1	4.23	1	4.65	1	4.14	2
Clash Detection	4.27	2	4.37	2	4.23	2	4.47	3	4.05	4
Decision Making	4.23	3	4.37	3	3.77	5	4.65	2	4.05	5
Scheduling	4.17	4	4.26	4	3.92	4	4.24	6	4.19	1
Site Progress Monitoring	4.11	5	4.16	6	3.69	6	4.41	4	4.10	3
Resource Alloc. & Waste Man.	4.09	6	4.05	9	4.08	3	4.24	7	4.00	6
Cost Management	4.01	7	4.16	7	3.62	7	4.24	8	3.95	7
Risk Management	3.99	8	4.21	5	3.46	8	4.35	5	3.81	8
Logistics and Supply-Chain	3.83	9	4.11	8	3.08	10	4.18	9	3.76	9
Safety Detection	3.83	10	3.95	10	3.38	9	4.18	10	3.71	10

To perform the first ANOVA test, the 70 participants were divided into the following groups according to their organizational structure: 19 academics, 13 customers, 17 contractors, and 21 consultants. In the evaluation of the questionnaire in which a total of 10 variables were rated, according to the aforementioned grouping, no statistically significant difference in opinion between these groups was found for 7 variables. However, it was observed that there was a statistically significant difference between groups in the variables of decision-making, risk management and logistics and supply chain according to the organizational structures of the participants. The p-value, which should not be greater than 0.05 to be able to say that a statistically significant difference exists, was observed for these three variables as 0.015, 0.021 and 0.020, respectively. The mean scores obtained for decision-making were 4.37 for academics, 3.77 for clients and developers, 4.65 for contractors and 4.05 for consultants. The mean scores for risk management appeared as 4.21, 3.46, 4.35 and 3.81 in the same order, and as 4.11, 3.08, 4.18 and 3.76 for the third variable, logistics and supply chain. The mean score rankings of all variables were generally close to each other between the overall rankings and the rankings according to the groups. However, some important differences were also observed. Clash detection, which was ranked second by all participants, was differentiated among consultants and ranked fourth in this group.

Decision-making was ranked third by academics, second by contractors, and fifth by clients and consultants. Scheduling was ranked 4th by academics and clients, 6th by contractors, and 1st by consultants. Resource allocation ranked 9th among academics and 3rd among clients. Risk management ranked 5th among academics and contractors and 8th among clients and consultants. Logistics and supply chain management ranked 8th among academics, 10th among clients, and 9th among contractors and consultants. Since there was a statistically significant difference between groups with p values less than 0.05 in ANOVA tests, post-hoc analyzes were performed to find out which groups caused this difference. To see which post-hoc test is appropriate, it is necessary to measure the homogeneity of variances. Levene's test was applied to Decision Making, Risk Management, and Logistics and Supply-Chain variables; and their homogeneity results are given in Table 4.8 . As seen in Table 4.8, the p-values of Levene's test were 0.076 and 0.541 for the risk management and logistics and supply-chain variables, respectively, and 0.026, which was lower than the significance level (0.05) for the decision-making variable. These values determined the tests to be applied to the variables. While the Games-Howell test was applied to the non-homogeneously distributed decision-making variances, the Gabriel's Test and the Tukey Test Range were applied to the other two variables which have homogeneously distributed variances.

Table 4.8 : Levene Statistic results for homogeneity of variances

Variables	Levene Statistic	Sig.
Decision Making	3.288	.026*
Risk Management	2.397	.076
Logistics and Supply-Chain	.724	.541

* Homogeneity test result is significant at the 0.05 level. $p < 0.05$

In the post-hoc test for the decision-making variable, the difference between the views of the contractor and consultant groups was found to be valid with a significance value of 0.025. With this result, it can be said that the p-value showing a significant difference in the ANOVA test performed for the variable is due to the difference between contractors and consultants. The results of the Games-Howell non-parametric post hoc test are given in Table 4.9.

Table 4.9 : Games-Howell post-hoc test results for decision-making variable.

Organizational Group (I)	Organizational Group (J)	Mean Difference (I-J)	Std. Error	Sig.
Academics	Client/Developer	.599	.350	.343
	Contractor	-.279	.212	.559
	Consultant	.321	.238	.538
Client/Developer	Academics	-.599	.350	.343
	Contractor	-.878	.326	.069
	Consultant	-.278	.343	.848
Contractor	Academics	.279	.212	.559
	Client/Developer	.878	.326	.069
	Consultant	.599	.201	.025*
Consultant	Academics	-.321	.238	.538
	Client/Developer	.278	.343	.848
	Contractor	-.599	.201	.025*

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

When grouped by organizational structure, the Gabriel's test and Tukey's test were applied as the second post hoc analysis of the study after controlling for homogeneity of variances of the remaining 2 variables showing a significant difference. The results were the same in both tests as given in Table 4.10 and Table 4.11. For the risk management variable, the reason for the statistically significant differences was the group of clients/developers and contractors in both tests, while for the logistics and supply chain variable, the results in both tests showed that clients/developers disagreed with both academics and contractors. In the Tukey test applied to risk management, the p-value of the interaction between the client/developer and contractor groups was 0.029, while this value was 0.033 in the Gabriel test. Further, in post-hoc tests for logistics and supply chain, the p-values of the Tukey and Gabriel tests were 0.034 and 0.038 for the client/developer and academic groups, and 0.024 and 0.28 for the client/developer and contractor groups, respectively.

Table 4.10 : Tukey’s and Gabriel’s post-hoc tests results for risk management variable.

Post-Hoc Tests	Organizational Group (I)	Organizational Group (J)	Mean Diff. (I-J)	Std. Error	Sig.
Tukey	Academics	Client/Developer	.749	.305	.077
		Contractor	-.142	.283	.958
		Consultant	.401	.269	.448
	Client/Developer	Academics	-.749	.305	.077
		Contractor	-.891	.313	.029*
		Consultant	-.348	.299	.653
	Contractor	Academics	.142	.283	.958
		Client/Developer	.891	.313	.029*
		Consultant	.543	.277	.212
	Consultant	Academics	-.401	.269	.448
		Client/Developer	.348	.299	.653
		Contractor	-.543	.277	.212
Academics	Client/Developer	.749	.305	.093	
	Contractor	-.142	.283	.997	
	Consultant	.401	.269	.586	
Gabriel	Client/Developer	Academics	-.749	.305	.093
		Contractor	-.891	.313	.033*
		Consultant	-.348	.299	.808
	Contractor	Academics	.142	.283	.997
		Client/Developer	.891	.313	.033*
		Consultant	.543	.277	.276
	Consultant	Academics	-.401	.269	.586
		Client/Developer	.348	.299	.808
		Contractor	-.543	.277	.276

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

Table 4.11 : Tukey’s and Gabriel’s post-hoc tests results for logistics and supply-chain variable.

Post-Hoc Tests	Organizational Group (I)	Organizational Group (J)	Mean Diff. (I-J)	Std. Error	Sig.
Tukey	Academics	Client/Developer	1.028	.368	.034*
		Contractor	-.071	.341	.997
		Consultant	.343	.324	.714
	Client/Developer	Academics	-1.028	.368	.034*
		Contractor	-1.100	.377	.024*
		Consultant	-.685	.361	.239
	Contractor	Academics	.071	.341	.997
		Client/Developer	1.100	.377	.024*
		Consultant	.415	.334	.602
	Consultant	Academics	-.343	.324	.714
		Client/Developer	.685	.361	.239
		Contractor	-.415	.334	.602
	Academics	Client/Developer	1.028	.368	.038*
		Contractor	-.071	.341	1.000
		Consultant	.343	.324	.868
Client/Developer	Academics	-1.028	.368	.038*	
	Contractor	-1.100	.377	.028*	
	Consultant	-.685	.361	.305	
Gabriel	Contractor	Academics	.071	.341	1.000
		Client/Developer	1.100	.377	.028*
		Consultant	.415	.334	.762
	Consultant	Academics	-.343	.324	.868
		Client/Developer	.685	.361	.305
		Contractor	-.415	.334	.762

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

The second grouping for applying the ANOVA test was done according to the experience of the participants. Participants were grouped into 5 different categories according to their years of experience: (1) less than 2 years, (2) 3-5 years, (3) 6-10 years, (4) 11-15 years, and lastly (5) more than 15 years. The results of the test are shown in Table 4.12 and rankings of mean scores depending on the results are given in Table 4.13.

Table 4.12 : ANOVA results for digital twin service variables by years of experience.

Variables	Groups exp.	N	Mean	Std. Deviation	f	p-value
Communication and Collaboration	Less than 2 yrs.	14	4.50	.650	1.224	.309
	3–5 years	12	4.42	.669		
	6–10 years	15	4.20	.862		
	11–15 years	10	4.70	.675		
	15+ years	19	4.11	.937		
Clash Detection	Less than 2 years	14	4.43	.756	2.264	.072
	3 – 5 years	12	4.42	.793		
	6 – 10 years	15	4.27	.799		
	11 – 15 years	10	4.80	.422		
	15+ years	19	3.79	1.316		
Decision Making	Less than 2 years	14	4.43	.646	1.778	.144
	3 – 5 years	12	4.42	.793		
	6 – 10 years	15	4.20	.676		
	11 – 15 years	10	4.50	.527		
	15+ years	19	3.84	1.068		
Scheduling	Less than 2 years	14	4.64	.497	3.499	.012*
	3 – 5 years	12	4.42	.669		
	6 – 10 years	15	3.80	.862		
	11 – 15 years	10	4.60	.699		
	15+ years	19	3.74	1.284		
Site Progress Monitoring	Less than 2 years	14	4.29	.726	.582	.677
	3 – 5 years	12	4.25	1.055		
	6 – 10 years	15	3.87	.915		
	11 – 15 years	10	4.20	.789		
	15+ years	19	4.05	.780		

Table 4.12 (continued) : ANOVA results for digital twin service variables by years of experience

Variables	Groups exp.	N	Mean	Std. Deviation	f	p-value
Resource Allocation	Less than 2 years	14	4.43	.756	2.405	.058
	3 – 5 years	12	4.25	.965		
	6 – 10 years	15	3.47	.990		
	11 – 15 years	10	4.30	.675		
	15+ years	19	4.11	1.049		
Cost Management	Less than 2 years	14	4.43	.756	1.535	.202
	3 – 5 years	12	3.67	1.155		
	6 – 10 years	15	3.80	1.082		
	11 – 15 years	10	4.40	.843		
	15+ years	19	3.89	1.100		
Risk Management	Less than 2 years	14	4.36	.745	1.758	.148
	3 – 5 years	12	4.25	.754		
	6 – 10 years	15	3.87	.743		
	11 – 15 years	10	4.00	.816		
	15+ years	19	3.63	1.116		
Logistics and Supply-Chain	Less than 2 years	14	4.29	.726	1.795	.140
	3 – 5 years	12	3.67	1.231		
	6 – 10 years	15	3.53	.834		
	11 – 15 years	10	4.30	.823		
	15+ years	19	3.58	1.346		
Safety	Less than 2 years	14	4.07	.730	1.711	.158
	3 – 5 years	12	3.67	1.073		
	6 – 10 years	15	3.60	1.183		
	11 – 15 years	10	4.50	.707		
	15+ years	19	3.58	1.261		

* ANOVA result is significant at the 0.05 level. $p < 0.05$

Table 4.13 : Rankings of the influence of the digital twin services by years of experience.

Variables	All		Less 2		3-5		6-10		11-15		15+	
	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank
Communication and Collab.	4.34	1	4.50	2	4.42	1	4.20	2	4.70	2	4.11	1
Clash Detection	4.27	2	4.43	3	4.42	2	4.27	1	4.80	1	3.79	6
Decision Making	4.23	3	4.43	4	4.42	3	4.20	3	4.50	4	3.84	5
Scheduling	4.17	4	4.64	1	4.42	4	3.80	6	4.60	3	3.74	7
Site Progress Monitoring	4.11	5	4.29	8	4.25	5	3.87	4	4.20	9	4.05	3
Resource Alloc. & Waste Man.	4.09	6	4.43	5	4.25	6	3.47	10	4.30	7	4.11	2
Cost Management	4.01	7	4.43	6	3.67	8	3.80	7	4.40	6	3.89	4
Risk Management	3.99	8	4.36	7	4.25	7	3.87	5	4.00	10	3.63	8
Logistics and Supply-Chain	3.83	9	4.29	9	3.67	9	3.53	9	4.30	8	3.58	9
Safety Detection	3.58	10	4.07	10	3.67	10	3.60	8	4.50	5	3.58	10

To perform the ANOVA test, the 70 participants were divided into 5 groups according to their years of experience. 14 participants have less than two years of experience, 12 participants have 3 to 5 years, 15 participants have 6 to 10 years, 10 participants have 11 to 15 years, and 19 participants have more than 15 years of experience. It can be said that the experience levels of the participants are distributed close to each other among the groups. In the ANOVA test, in which the digital twin services were determined as a variable, it was found that the approach to other variables, except scheduling, did not show a statistically significant difference between the groups within this grouping. For the variable with a p-value of 0.012, it can be said that the view on this variable is statistically different between the groups. Scheduling was the 4th variable with the highest mean ranking with a mean score of 4.17. However, the first group of experts with less than 2 years of experience rated scheduling with a mean score of 4.64, while the experts with 3-5 years of experience rated it with a mean score of 4.42, the experts with 6-10 years of experience with a mean score of 3.80, the experts with 11-15 years of experience with a mean score of 4.60, and the experts with more than 15 years of experience with a mean score of 3.74. Even though there is no

statistically significant difference, it may be useful to evaluate the resource allocation and waste management variable, which has a p-value of 0.058, as it is close to 0.05. For this variable, the highest mean score of 4.43 was rated by experts with less than two years of experience, while the mean score of experts with 6-10 years of experience was 3.47. When the table of the rankings of mean scores according to the same grouping is examined, even though it seems normal in general, remarkable rankings are also found. Although clash detection ranked second in the overall rankings, experts with more than 15 years of experience ranked it 6th. While those with less than two years of experience ranked the scheduling variable 1st, the group with more than 15 years of experience placed it 7th. Site progress monitoring ranked 8th among the group with the least experience, but 3rd among the group with the most experience. Resource allocation ranked 10th among those with 6-10 years of experience and 2nd among those with more than 15 years of experience. Safety detection, on the other hand, was ranked 5th by experts with 11-15 years of experience, although it ranked last on average.

Similarly, post-hoc analyzes were conducted for variables that showed a statistically significant difference between groups in tests that grouped respondents' experiences. Since the only significant difference was only seen in scheduling among the ten variables, the homogeneity of variances was measured by performing Levene's test for only this variable. The p-value of Levene's test for the variable scheduling was below the significance level and was 0.003 (Table 4.14). Since the variances of the variable were distributed non-homogeneously, it was decided to perform the Games-Howell test.

Table 4.14 : Levene Statistic results for homogeneity of variances for scheduling.

Variable	Levene Statistic	Sig.
Influence of Scheduling	4.367	.003*

* Homogeneity test result is significant at the 0.05 level. $p < 0.05$

In the post-hoc test for the scheduling variable, a statistically significant difference between experts with less than 2 years of experience and experts with 6-10 years of experience was found to be valid with a significance value of 0.027. The results of the Games-Howell non-parametric post hoc test are given in Table 4.15.

Table 4.15 : Games-Howell post-hoc test results for scheduling variable.

Group by Years of Exp. (I)	Group by Years of Exp. (J)	Mean Difference (I-J)	Std. Error	Sig.
Less than 2 years	3 – 5 years	.226	.234	.867
	6 – 10 years	.843	.259	.027*
	11 - 15 years	.043	.258	1.000
	15+ years	.906	.323	.067
3 – 5 years	Less than 2 years	-.226	.234	.867
	6 – 10 years	.617	.295	.254
	11 – 15 years	-.183	.293	.969
	15+ years	.680	.352	.325
6 – 10 years	Less than 2 years	-.843	.259	.027*
	3 – 5 years	-.617	.295	.254
	11 – 15 years	-.800	.314	.115
	15+ years	.063	.369	1.000
11 – 15 years	Less than 2 years	-.043	.258	1.000
	3 – 5 years	.183	.293	.969
	6 – 10 years	.800	.314	.115
	15+ years	.863	.368	.162
15+ years	Less than 2 years	-.906	.323	.067
	3 – 5 years	-.680	.352	.325
	6 – 10 years	-.063	.369	1.000
	11 – 15 years	-.863	.368	.162

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

With this result, it can be said that the p-value that showed a significant difference in the ANOVA test performed with the relationship between the mentioned variable and the experience level is due to the difference in opinions between these two groups with different experience levels.



5. DISCUSSIONS AND CONCLUSION

Although the construction industry plays a vital role in the economy, it remains rather weak compared to other industries in terms of levels and increase rate of productivity. To face this, a quest has emerged in the construction industry to benefit from digital tools by following other industries as an improved construction project management is the only way to tackle this problem. The age of digital transformation, which brings many interrelated elements such as competition, changing customer demands, new-generation employees and stakeholders, has also offered new instruments that are rapidly spreading to offer enhanced construction project management. After the spread of the fact that digital tools provide advantages in many industries, on the way to becoming a more successful industry, the construction industry was also able to integrate digital tools into pre-construction processes and achieved a late but rapid adaptation by obtaining very positive outputs. However, the industry has not been able to bring these developments to the same extent in the post-design phases.

Considered one of the biggest and most important steps in the digitalization journey of the construction industry, Building Information Modeling has acted as a catalyst for efforts to automate the industry. However, constantly developing technologies and emerging opportunities paved the way for newer concepts to enter the industry. The digital twin, which is defined as a virtual system that connects design, construction, and operation by using a combination of technologies to connect physical and real assets bidirectionally, has started to be examined in the construction industry literature as one of the new instruments offered by the aforementioned digital transformation era. Contrary to the literature, the digital twin, which uses the model offered by BIM as a digital database and takes it to the next level with physical and real-time data, is seen as a closed box for industry professionals since even BIM has not yet been fully adopted in the industry. Concurrently, the literature on construction project management also lacks understanding regarding the digitalisation of post-design phases. At this point, this study aimed to clarify the relationship between the digital twin and BIM from the perspective of construction project management to investigate the influences of the digital twin in the construction phase of the project lifecycle.

Because it is obvious from experience in other industries that the construction industry also needs to enhance its management understanding to produce better figures.

In line with this aim, the digital twin concept was defined and its characteristics, practices, and the place of technologies integrated into it in the construction industry is revealed and explained in context with construction project management. Also applications and functions of during the construction phase of the building life cycle, which revealed that the literature needs more research, were examined. Since BIM, which is the most up-to-date step in the digitalization process of the industry, is a bridge for the transition to the digital twin and an element to be learned from, the opinions of BIM experts were taken about the digital twin during construction services in the literature. Thus, by examining what the literature offers and their value according to professionals, it is revealed how and to what extent the digital twin can improve BIM within the framework of project and construction management.

A comprehensive literature study was conducted to reveal the characteristic structure and applications of the digital twin concept within the framework of the construction industry. The most effective technologies that support the concept and find application areas for themselves were found as the internet of things (IoT), artificial intelligence (AI), augmented reality (AR), virtual reality (VR), and blockchain -generally examined together with smart contracts-. In the relevant literature, which consists of recent studies only in the last few years, the digital twin concept provides very effective advantages, while at the same time it offers applications in every stage of the project life cycle except the demolition. However, although construction project management literature studies related to the design phase or transition from BIM to digital twin exist, a knowledge gap has been observed regarding the digital twin technology in post-design phases and its broad applicability in the field, especially for the construction process. So to contribute to filling this gap, digital twin during construction has been scrutinized. A detailed background analysis was performed to find out and discuss the digital twin relationship with BIM, and the functions and applications of both in the construction. After that, ten digital twin services for construction that addresses enhanced construction project management with the potential for further improvement of BIM were compiled in the literature. These are site progress monitoring, resource allocation and waste management, clash detection, decision-making, communication and collaboration, cost management, scheduling,

risk management, logistics and supply chain, and safety detection. Since the goal of construction project management is to provide effective management of the project's schedule, cost, quality, safety, scope, and function, it is obvious that each of the services is an important aspect of construction project management that need serious consideration for a manager. To measure the validity and importance for industry professionals of these ten digital twin services, a questionnaire survey was conducted sampling BIM experts, who have the most acceptable experience in the digitalization journey of the industry.

The questionnaire with the valid participation of 70 BIM experts, gathered information with a 5-point Likert scale about the influence of ten digital twin services on parallel BIM uses that address construction project management practices. The validity and examination of the study, which can be accepted as international thanks to both domestic and foreign participants, is ensured by a series of sequential statistical tools such as Cronbach's alpha reliability test, Skewness-Kurtosis normality distribution test and Pearson's bivariate correlation analysis. Further analysis was conducted by performing independent-samples t-tests for comparing experts' opinions. One-way ANOVA was another analysis that was applied to see the different perceptions. Finally, to uncover statistically significant differences between groups, appropriate post-hoc tests -namely Games-Howell test, Gabriel's test, and Tukey test-were applied. Levene's test was applied to measure the homogeneity of variances before post-hoc analyses.

According to the results of the questionnaire, ten digital twin services that found applications in the construction are ranked as follows according to the mean scores of their influences on BIM uses in parallel with them: (1st) 4.34 with communication and collaboration; (2nd) clash detection with 4.27; (3rd) decision-making with 4.23; (4th) scheduling with 4.17; (5th) Site progress monitoring with 4.11; (6th) with 4.09 resource allocation and waste management; (7th) cost management with 4.01; (8th) risk management with 3.99; and safety detection with logistics and supply chain with a common mean score of 3.83. High mean scores of all ten variables show that participants attach great importance to the specified digital twin services. The fact that these services, which are stated to provide significant advantages in the literature, are also valued by industry professionals and their influences are highly rated. The results of this study are consistent with those of other studies which presented the advantages

of digital twin services in the construction (Alheeti & Aldaiyat, 2021; Baduge et al., 2022; Boje et al., 2020; Dallasega et al., 2020; Darabseh & Martins, 2020; Greif et al., 2020; Z. H. Han et al., 2020; Hooda et al., 2021; F. Jiang et al., 2021; Y. Jiang, 2021; J. Kim & Irizarry, 2021; Nguyen, 2021; Oke et al., 2020; Opoku et al., 2021; Tayeh & Issa, 2020; Xu, 2021). According to the digital construction professionals, it was observed that the construction project management service that the digital twin could improve the BIM the most in the construction was communication and collaboration with 4.34 score. The real-time model and data visualization tools offered by the digital twin have proven to make a critical difference in communication, collaboration and trust between project participants compared to BIM's as-design model. The clash detection service, which follows it, has emerged as the second service that will have the greatest influence, according to experts, with a mean score of 4.27. To avoid calendar, cost, resource and site conflicts, the digital twin's ability to instantly monitor any desired element precludes BIM's improved planning models offered at 4D or 5D levels. The most important factors affecting this score may be the human factor, which has to take an active role in BIM processes, and question marks about the model's completion. The automated sensing capability of the digital twin overcomes these downsides and presents an as-is model to the project participants, allowing alternative plans and simulations. Although the logistics and supply-chain service is considered one of the most important services of the digital twin for Opoku et al. (2021) and Boje et al. (2020), it has been accepted as one of the two services with the lowest impact among other services with a mean score of 3.83 for industry professionals. With this result, it can be said that the follow-up of an item to be transported at the construction site since the point of production and/or a system in which the supply-chain actors are more integrated have a lower effect on BIM uses for logistics and supply chain management. The safety detection service with an equal mean score has also been considered to have a lower impact compared to other services, although it shows that -thanks to its instantaneous monitoring of the construction site- the digital twin can go beyond the safety planning provided by the BIM model, which creates disadvantages in constantly changing conditions. When the interrelationships of the influences of all ten digital twin services on parallel BIM uses regarding the construction project management are examined, as expected, most of the variables were found to be correlated in the range of 0.310 to 0.729 with a two-tailed correlation significant at 0.01 level. This strong relationship has emerged as it is known that whole construction

project management is an interrelated and comprehensive process but also, it has been revealed that elements should be considered as a whole in which they are in a bidirectional relationship with each other for an enhanced management during construction.

Further analysis investigated the relationship between the perceptions of the participants. Accordingly, participants were divided into meaningful groups, and it was searched whether there was any statistically significant difference between the groups. The first grouping was composed according to the participants' countries, and their perceptions of the digital twin services were analysed. The analysis revealed that, while there was a statistically significant difference between domestic and international experts on scheduling; no significant difference was found on the remaining nine services. Since both groups assigned high rates (the mean score for domestic experts was 4.40, this score for foreign experts was 3.94) for the specified digital twin services, it can be said that both groups think that the digital twin has a significant positive impact on 4D BIM applications. The scheduling service of the digital twin exists with the support of artificial intelligence. The fact that artificial intelligence applications have not yet found enough space in practice may have caused this difference in the evaluation of potential between groups. The second grouping was made according to whether the participants were users of digital twins or not. Critically, the emergence of the same opinions about all services shows that there is no inconsistency between what the digital twin claims to offer and what it can deliver. This will reduce the question marks for professionals who want to catch up in this field and for institutions that want to adopt digital twin technologies.

In the analysis that divided the participants into more than two groups according to their organizational structure, decision-making as a construction project management practice, was the first digital twin service that has seen a significant difference between groups. In further analysis, it was revealed that this difference emerged from the opinions of contractors and consultants. While the mean score of the contractors was 4.65, it decreased to 4.05 for the consultants. Risk management has been the second service where experts have not been able to fully agree on the impact of its parallel BIM uses. The statistically significant difference here has emerged this time between clients/developers and contractors. For the third service, logistics and supply chain, it was seen that the difference was since the clients and developers with a 3.08 mean

score could not along with the academics with a 4.11 mean score and the contractors with a 4.18 mean score. A difference of opinion cannot be generalized between any two particular groups, since all three differences of opinion are experienced between different pairs. In addition, even though each group approaches the project with different risks, different objectives and different perspectives, the fact that there are differences of opinion for only a few services in this combination of relationships has been an indication that the positive influence of the digital twin has been accepted by nearly all stakeholders of the industry. In the second large group analysis of the experience levels of the participants, the only statistically significant difference was in scheduling among the influences of digital twin services. Only among experts with less than 2 years of experience and experts with 6 to 10 years of experience. The fact that there was no significant difference between the experts from different experience levels showed that there is a common agreement on the positive influence potential of the digital twin. The findings support previous researches in the digital construction area.

Some suggestions for future studies on the digital twin might be to identify the barriers for faster adaptation of this concept to industry practice and to question what should be done to overcome these barriers. In addition, taking the BIM process as an example can be an important opportunity in this direction.

The digital twin services, those positive effects have been examined in the literature, were scrutinized in the construction with the motivation of filling a knowledge gap, and the theory and industry views were tried to be superposed. The results of this study have contributed to and strengthened the construction project management literature due to its limited knowledge of the digital twin. In line with the data that this research sheds light on, it has been revealed that the potential uses and expected advantages of the digital twin on construction project management revealed by the researchers, are evaluated in the same way for experienced digital construction professionals in the industry. Thus, it can be concluded that the industry should benefit from the digital twin services for enhanced construction project management, which can get rid of the low efficiency and lack of productivity that the construction industry is still experiencing. This study serves as a source of motivation for researchers working in the field of digital construction and a guide for construction project managers, industry professionals and institutions with question marks about concepts and outcomes.

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APPENDICES

APPENDIX A: Questionnaire “Digital Twin Influence on BIM: a Construction Management Perspective”



APPENDIX A

Digital Twin Influence on BIM: a *Construction Management Perspective*

This questionnaire is part of an MSc thesis research examining the influence of "Digital Twin" services on "Building Information Modeling" uses at the construction phase within the architecture, engineering, construction, and operation (AECO) industry.

We have attached a two-part questionnaire. The first part of the questionnaire captures general information about respondents. The second part gathers information about the influence of Digital Twin services on BIM uses. We want to assure you that the information we collect from you will be used for research purposes only and will be held in the strictest confidence.

Thank you for your time and your valuable contribution. If you have any queries, you are most welcome to contact:

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* Gerekli

What is your profession? *

- Architecture
- Civil Engineering
- Electrical Engineering
- Mechanical Engineering
- Diğer: _____

What is the highest degree you have completed? *

- Bachelor
- Studying for Master
- Master
- Studying for Doctorate
- Doctorate
- Diğer: _____

Please indicate your years of experience in the AECO industry? *

- Less than 2 years
- 3 - 5 years
- 6 - 10 years
- 11 - 15 years
- 15+ years

Please indicate the organization you associate with. *

- Academic institution
- Client / developer
- Contractor
- Consultant
- Other: _____

In which country do you / your company operate? *

Yanıtınız _____

What is your role/title in your company? *

Yanıtınız _____

Do you use any Digital Twin practice in your company? *

- Yes
- No

Please indicate your years of experience in the BIM or Digital Twin fields? *

- Less than 1 year
- 1 - 2 years
- 3 - 5 years
- 5 - 10 years
- 10+ years

What is the Digital Twin? (If you need)

The digital twin concept is continual and bidirectional data stream between a physical asset and its virtual representation. It is embodied in three main elements: physical entity in the real world (1), its virtual counterpart in a digital environment (2), and a data flow that connects both (3). Unlike BIM, it allows to real-time monitoring of a building and other construction assets via its digital representation with variety of tools such as IoT, AI, RFID tags, mobile devices etc.

Influence of "Digital Twin" services on "Building Information Modeling" uses at the construction phase from a construction management perspective

This section of the questionnaire compiles ten BIM-supported areas that have the potential for further improvement with digital twin services, according to the literature.

Please rate the potential influences of digital twin services (each explained below) on a scale of 1 to 5 based on your experience (1; not effective; 2; slightly effective; 3; moderately effective; 4; very effective; 5; extremely effective).

Influence on Site Progress Monitoring *

Digital twin technologies provide continuous and real-time data flow from the site to the model by automating the site monitoring process without requiring human in the hand-held tools such as photogrammetry, laser scanning, and drones, and without the human need to process the obtained the enormous amount of data which is both challenging and time-consuming to make sense of, validate, and interpret, and ultimately process it in an effective manner to facilitate real-time responses.

1 2 3 4 5

not effective extremely effective

Influence on Resource Allocation and Monitoring (labor, equipment, material) and Waste Management *

With the digital twin sensors and mobile technologies, any desired resource such as worker, material, machinery in the construction site can be monitored on the virtual model. It provides the opportunity to make instant interventions by displaying the instant and real situations, positions and movements of the resources in the dynamic construction site environment instead of the planned locations.

1 2 3 4 5

not effective extremely effective

Influence on **Clash Detection** *

Automated sensing with digital twin avoids the question marks about the model's completion, validity and human factor of BIM adoption for clash management. It enriches the BIM model by reflecting the instant situation (as-is) and allows professionals to make alternative (what-if) planning simulations including building tasks as well as temporary logistics activities etc. Provides an opportunity to examine the interaction of temporary construction sites and objects with existing and newly built areas.



Influence on **Decision Making** *

A "real-time virtual model" which is provided with up-to-date, instant, cross-checking and cross-referencing data by multiple digital twin sources and technologies prevents "drowning in data" situation of as-design model caused by enormous amount of data from the construction site. With AI or various computer software, instant data can be visualized according to the relevant user and make any data understandable and processable. Thus, it offers more valuable information to stakeholders and decision-making processes.



Influence on **Communication and Collaboration** *

A "real-time virtual model" which is provided with up-to-date, instant, cross-checking and cross-referencing data by multiple digital twin sources and technologies prevents "drowning in data" situation of as-design model caused by enormous amount of data from the construction site. With AI or various computer software, instant data can be visualized according to the relevant user and make any data understandable and processable. Thus, it offers more valuable information to stakeholders and decision-making processes.



Influence on **Cost Management** *

To improve 5D BIM dimension with the aim of keeping costs at an estimated level, digital twin uncovers and analyzes costs and provides precise cost estimations using real-time data and machine learning. Also can inform the managers about the errors and their causes at the right time to improve the management at the construction phase by running the correct artificial intelligence algorithms predetermined according to the instant changes of construction site dynamics like over-employment.



Influence on Scheduling *

To improve 4D dimension with the aim of utilizing resources correctly, with a more complex structure, digital twin reduces workload on tasks require time for a human, uses newly developed time management tools like 'smart critical path method' and inform the managers about the errors and their causes at the right time to improve the management at the construction phase by artificial intelligence considering instant changes of construction site dynamics like too long production time.

1 2 3 4 5

not effective extremely effective

Influence on Risk Management *

A "real-time virtual model" which is provided with up-to-date, instant, cross-checking and cross-referencing data by multiple digital twin sources and technologies avoids the the effort and waste of time in processing and response the measurements and controls carried out for the risk management plan. Values decided in risk planning are answered with artificial intelligence algorithms such as artificial neural network (ANN) to reveal potential risks and turn them into actionable notifications for managers.

1 2 3 4 5

not effective extremely effective

Influence on Construction Logistics and Supply-Chain *

Improving the management of the logistics network requires an inclusive supply chain, in which tasks such as the delivery of materials and equipment connected with their prerequisites. Digital twin enhance the as-designed model and enable a pro-active modeling, eliminate the lack of integration of on-site and off-site supply chain actors, monitor layouts of construction site, update real-time location of the resources, enable the tracking of an ordered material from the factory to the construction site, and give professionals an optimized duration and sequence recommendations.

1 2 3 4 5

not effective extremely effective

Influence on Safety Detection *

Implementation process of the safety management workflow is insufficient due to the existing data acquisition from the construction site and their processing methods. In addition, subcontracting concept and temporary workers cause the use of BIM to be neglected or continuous data changes.

Digital twin collects information on the presence of workers on-site and checks their compliance to safety rules like wearing helmets and detect motionlessness or fall behaviors. It provides a healthier working environment by monitoring data such as air quality and temperature in the working areas. Virtual simulations of evacuations and site safety may also shed additional light on previously unanticipated near-term safety threats and dangers.

1 2 3 4 5

not effective extremely effective

Please feel free to leave any final comments relating to the influence of the Digital Twin on construction management during the construction phase with considering the BIM technology.

Yantınız _____

Please provide your email address if you would like to receive a summary of the research findings.

Yantınız _____





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