2021-05-01

Digital Twin Technology Applications For Transportation Infrastructure - A Survey-Based Study

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DIGITAL TWIN TECHNOLOGY APPLICATIONS FOR TRANSPORTATION INFRASTRUCTURE – A SURVEY-BASED STUDY

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2021

DEDICATION

I dedicate my thesis to my family. A special feeling of gratitude to my mom, Cynthia Lopez, because without her none of this would have been possible, to my wife Vianney Valtierra for always supporting me and to my brothers Kevin Cruz and Abraham Cazares who always inspired me to keep pursuing my academic goals.

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by

HECTOR CRUZ, B.S.

THESIS

Presented to the Faculty of the Graduate School of

The University of Texas at El Paso

in Partial Fulfillment

of the requirements

for the Degree of

MASTER OF SCIENCE

Department of Civil Engineering

THE UNIVERSITY OF TEXAS AT EL PASO

May 2021

ACKNOWLEDGEMENTS

I would like to express my profound appreciation and sincere thanks to Dr. Soheil Nazarian for his invaluable inspiration and guidance throughout this process. This thesis would have not been possible without his advice, continuous support, and persistent encouragement. I am grateful to him not only for his exceptional mentorship but also for his major contribution to the development of my character as a young engineer.

Special acknowledgment to Dr. Adeebah Raheem for her appreciated assistance during all the stages of this study. Her recommendations and feedback have contributed to the improvement of this research.

Finally, I would like to thank Dr. Bill Tseng for serving on my committee and providing me with comments on my thesis.

ABSTRACT

In the past couple of decades, various industries have taken advantage of emerging advanced technologies, such as digital twin (DT), to find more effective solutions in their respective areas. In the transportation infrastructure sector, the concept and implementation of DT technologies are slowly gaining traction but lagging behind other major industries. To better understand the limitations, opportunities and challenges for the adoption of DT in this sector, a survey questionnaire was distributed to collect information from industry professionals involved in transportation infrastructure projects. The purpose of this study is to understand how DT technology is being perceived by the industry. Based on the results of this survey, the current state of DT in the infrastructure sector, as well as the expected benefits, and potential challenges for the deployment of DT are discussed here. This study aims to initiate discussion for future research in DT technologies for transportation infrastructure applications.

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CHAPTER 1: INTRODUCTION

The digital revolution during the last couple of decades has transformed numerous industries by improving communication and increasing productivity. The pace of innovation has been remarkable in many sectors, including health sciences, education, and manufacturing. Emerging technologies, such as robotics, advanced computerized design, or predictive models have helped to create a digitized global industry that is now more productive, cost-effective, and sustainable (WEF, 2016). Compared to other major industries, the construction sector has been slow to adopt and adapt to new technologies (El Jazzar et al., 2020). Although traditional construction tools have worked for civil engineers in the past, most of these technologies cannot ensure consistent quality for construction projects. As a result, there has been a significant push in recent years for the implementation of new technologically advanced equipment and approaches that will contribute to considerable improvements in the quality, safety, and cost-effectiveness of infrastructure construction (Michalis 2019).

Digital twin (DT) technology is one of the numerous emerging technologies that can improve the decision-making process through better utilization of available data. According to The Institution of Engineering and Technology (IET), the DT is perceived as an essential technology that every company in the engineering field must utilize as this technology has the potential to provide remarkable benefits that could not be accomplished using traditional methods (IET, 2019). Despite the several advantages that DT systems can bring to the different agencies and companies in this industry, the technology is still underutilized for infrastructure applications (Fanning et al., 2015). To this date, the reasons for the industry not adopting this innovative technology can vary from case to case and from company to company. A comprehensive study is needed to investigate the current state of DT technologies for applications during the life-cycle of a transportation asset, as well as the different factors that are preventing the industry stakeholders from implementing twin solutions at a full-scale for infrastructure projects.

1.1 Problem Statement

The term ‘digital twin’ (DT) is gaining popularity across a wide variety of global industries. Some of the most advanced deployment of DT technology is currently taking place in the manufacturing sector, ao Similarly, other major industries are leveraging DT technologies to discover new solutions and optimize their operations (Gerber et al., 2019). In the infrastructure sector, the DT technology promises more effective asset design, project execution, and asset operations (IET, 2019). Yet, many challenges still exist for the effective implementation of this technology. Once the existing barriers are addressed, the results are expected to be profound (Gerber et al., 2019). Therefore, a comprehensive study is needed to determine potential solutions to accomplish a successful DT execution for applications in the infrastructure sector.

1.2 Purpose of Study

This research aims to assist the government, industry, and academia in determining the potential challenges and limitations that infrastructure stakeholders could face for the full-scale adoption of the DT technology. This study presents the responses of industry professionals involved in transportation infrastructure projects to a DT survey questionnaire. Based on the responses to the survey, this study will provide the basis for future research in this area. A survey questionnaire was designed and consisted of questions to collect the following information:

- Number of years since the company of the industry professional started using BIM technologies (BIM is an important component of a DT)
- The number of industry professionals that are familiar with the DT concept
- Number of companies considering implementing DT for future projects

- Industry professionals’ expected benefits from DT
- Potential challenges for the development and implementation of DT technologies in the infrastructure sector

1.3 Outline of Report

Besides this chapter, the thesis contains three chapters.

Chapter 2 consists of a comprehensive literature review of some of the main technologies that a DT is based on, namely Building Information Modeling (BIM), Artificial Intelligence (AI), the Internet of Things (IoT), and smart sensors. That chapter also presents various definitions of the DT technology and its potential applications in the infrastructure sector.

Chapter 3 explains the methodology followed for the preparation of a DT survey. That chapter also presents the responses of the industry professionals who participated in answering the survey and describes the findings.

Chapter 4 summarizes the conclusions, remarks, and recommendations drawn from this study, and discusses future research directions.

CHAPTER 2: LITERATURE REVIEW

The fourth industrial revolution, Industry 4.0, has introduced several new innovative technologies for applications in different disciplines. One of the most advanced technologies resulting from Industry 4.0 is the digital twin (DT). A DT is a virtual entity supported by Building Information Modeling (BIM), Artificial Intelligence (AI), the Internet of Things (IoT), and an abundance of data obtained from smart sensors. The technology helps in creating a digital representation of the physical object (Hinduja and Kekkar, 2020). This chapter includes a comprehensive literature review of Civil Infrastructure 4.0 (Industry 4.0 in the infrastructure sector) and various other technologies that may be incorporated into a DT. Definitions of DT, applications, and other related information regarding this technology will also be discussed in this chapter.

2.1 Transportation Infrastructure and Digitalization

Infrastructure is a critical component of a nation's development, which supports economic growth, improves the quality of life, and is crucial for public security (Palei, 2015). The construction of transportation infrastructure systems facilitates the efficient movement of goods and services, connects supply chains, and decreases the operating costs across a diverse group of industries (Oberhelman, 2015). However, the infrastructure sector lags behind other major industries in the adoption of these technological advances (El Jazzar et al., 2020). As the population continues to grow and transportation infrastructure ages, there is a greater need to implement innovative and more efficient methods to construct, maintain, and renovate infrastructure. Therefore, numerous researchers and organizations are promoting the adoption of new technologies to overcome the existing challenges to improve infrastructure (Michalis et al, 2019).

2.1.1 Industry 4.0

The manufacturing sector has witnessed three past industrial revolutions, as observed in Figure 2.1, that have led to changes of paradigm in this domain (Osunsanmi et al., 2018). The first industrial revolution involved mechanization through water and steam power. The second industrial revolution was triggered by electrification that enabled industrialization and mass production. The third industrial revolution is characterized by digitalization and the introduction of automation and microelectronics (Tay et al., 2018). During the last decade, the development of advanced communication technologies, devices connected to the internet, and data analytics has been occurring at a faster pace than any other time before, initiating the transition to the fourth industrial revolution, also known as Industry 4.0. The concept of Industry 4.0 was coined by the German Federal Government in January 2011 to highlight the beginning of the fourth industrial revolution and refer to the technological evolution from embedded systems to cyber-physical systems (Macdougall, 2018).

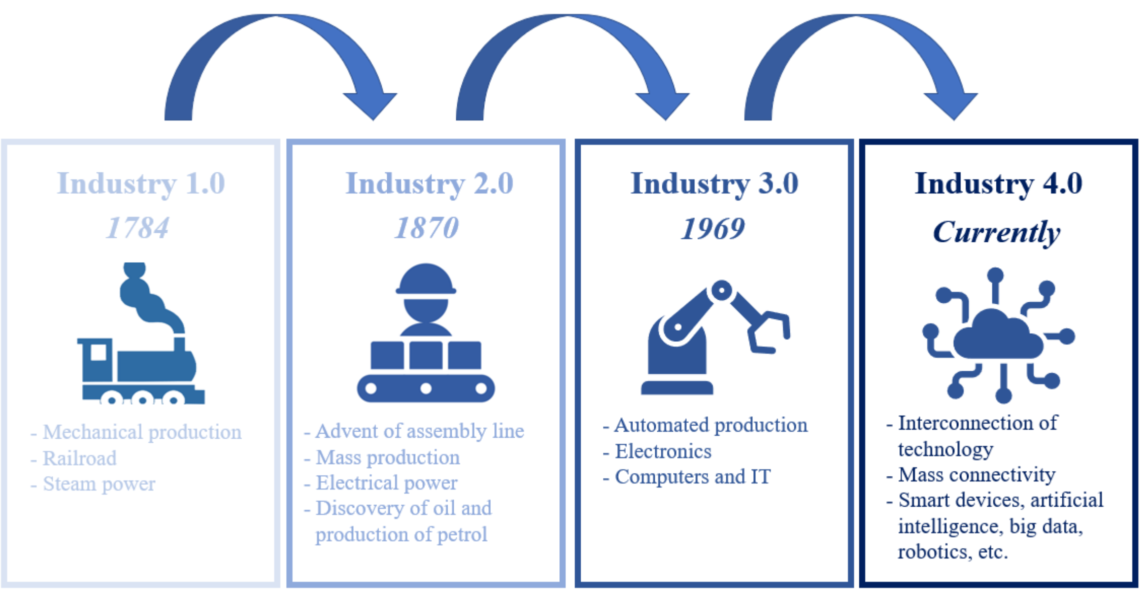

Figure 2.1 The industrial revolution (adapted from Tay et al., 2018)

Cyber-physical systems and the IoT form the basis of Industry 4.0 and are essential components to create a smart factory, the heart of Industry 4.0 (Hozdić, 2015). Cyber-physical systems are integrations of computation, networking, and physical processes with the capabilities to map the physical world into the virtual world (Lee, 2008; Nagy et al., 2018). An Industry 4.0 smart factory consists of several cyber-physical systems, which receive inputs from sensors to create a smart control loop capable of adaptation and autonomy (Zanero 2017; Michalis et al., 2019). In essence, Industry 4.0 deals with creating more digitalized systems and network integration via smart technologies (Erboz, 2017).

2.1.2 Civil Infrastructure 4.0

Due to the success of Industry 4.0 in the manufacturing sector, its concept has been rapidly extending to various fields, such as the automotive, finance, and healthcare industry (Osunsanmi et al., 2018). Recently, the infrastructure sector has also adopted the concept of Industry 4.0, creating a new term entitled Civil Infrastructure 4.0 (CI4.0). Similar to Industry 4.0, CI4.0 refers to the emergence of advanced technologies during the fourth industrial revolution, but in this case, with applications in the infrastructure sector. According to Michalis et al. (2019), CI4.0 has been characterized by the use of smart sensors to collect data, which are processed and used for optimized actions in real-time. The processing and use of these data enable autonomous, adaptive, and collaborative capabilities in infrastructure systems, with minimal human intervention required.

Figure 2.2 shows the typical advantages of implementing advanced technologies that have emerged during CI4.0. Some of the most distinguished technologies from CI4.0 include smart sensing, AI, real-time decision support systems, IoT, cybersecurity, cloud computing, big data, augmented reality, and interoperability with other infrastructure systems and end-users (Michalis et al., 2019). The innovative technologies emerging during CI4.0 have the potential to improve the different stages of infrastructure projects, resulting in decreased construction and maintenance costs, reduced damage, and increased quality of service towards effective and efficient transport systems with minimum disruptions (Michalis et al., 2019).

Figure 2.2 Benefits obtained from innovative technologies emerging during CI4.0 (Modified from Michalis et al., 2019)

2.2 Building Information Modeling

During the last couple of decades, civil infrastructure has continuously been growing around the globe due to the considerable increase in population and the need for replacing transportation infrastructure components that already passed their design age (Strategic Foresight Initiative, 2011). As a result, a significant push for the development and adoption of advanced technologies has been continuously occurring in the transportation sector. Although a variety of innovative technologies are starting to emerge for distinct applications within different phases of an infrastructure project, one technology that is revolutionizing the process of construction is known as Building Information Modeling or BIM (Biancardo et al., 2020). The concept of BIM was introduced in 1970 by Professor Charles Eastman at Georgia Tech School of Architecture. Figure 2.3 shows the development of BIM definitions from 1975 to 2013. Since then, the scope has broadened to cover various project aspects, such as design, estimation, construction process, building life cycle, performance, and technology (Latiffi et al., 2013) .

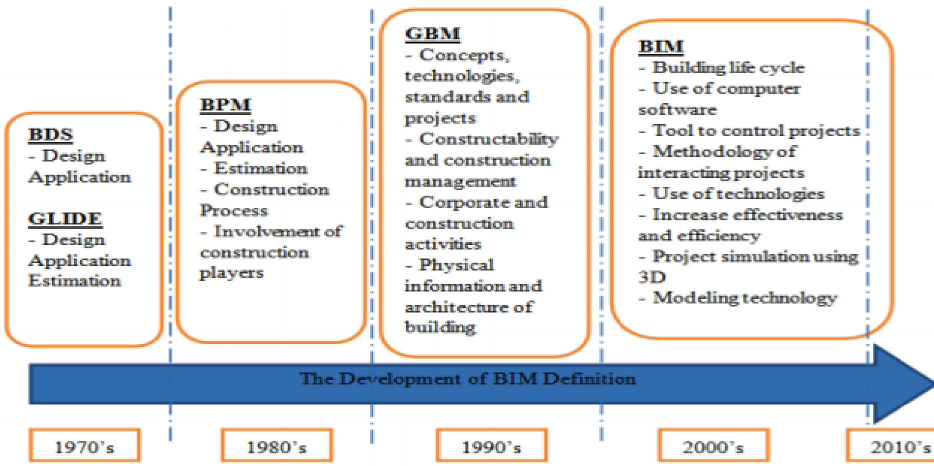

Figure 2.3 The development of BIM definition from 1975 to 2013 (Latiffi et al., 2013)

The U.S. National Building Information Model Standard Project Committee defined BIM as a "digital representation of physical and functional characteristics of a facility. BIM serves as a shared knowledge resource for information about a facility forming a reliable basis for decisions during its life-cycle from inception onward." As shown in Figure 2.4, BIM applications can provide improvements during the phases of design, construction, and operations. In essence, BIM is a computer-generated model that simulates the phases of a construction project digitally, contributing to more efficient design and documentation, better coordination, and improved visualization (Autodesk, 2017). When a change is made to the structure model by any party involved in the project, all graphical views (plan, elevation, detail, and other construction drawings), as well as non-graphical views (design documents, schedules, cost estimation), automatically reflect the change (Boukara and Naamane, 2015).

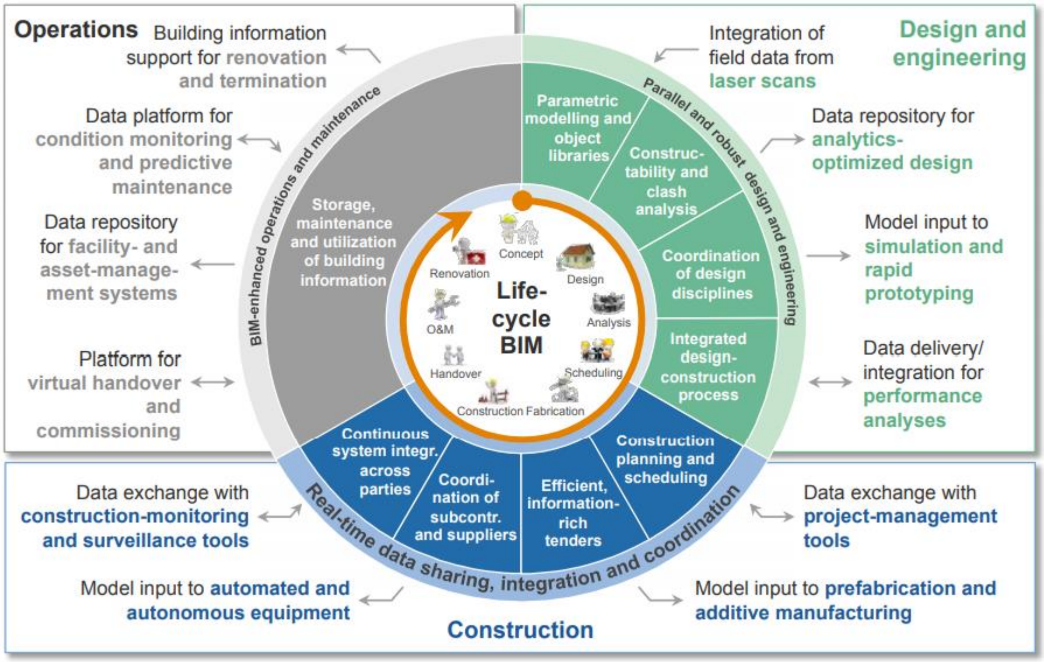

Figure 2.4 Applications of BIM through the life-cycle of a construction project (WEF, 2016)

BIM brings the construction industry to the next level by providing solutions that result in optimized design using the cloud, AI technologies, and modern collaboration features. The cloud-based model acts as a platform where survey, engineering, and construction data can all be tightly integrated. Once integrated, the design teams can utilize these data to perform advanced analytics, answer "what if" scenarios, create advanced simulations, and observe visualizations to further improve the design. BIM systems also allow different teams working on the project to collaborate from any location in real-time on the same design by simplifying the process of communicating and informing project decisions even to stakeholders who are not physically present on-site (BSA Foundation, 2017). Despite its numerous applications throughout a building life-cycle, BIM is usually distinguished for its capability to generate high-quality three-dimensional (3D) design schemes, support four-dimensional (4D) scheduling and five-dimensional (5D) cost estimation, and optimize facility management and maintenance (Shou et al. 2015).

2.2.1 BIM market and major players

BIM is usually used by real estate companies, construction firms, and AEC (architecture, engineering, and construction) professionals for improving the overall quality of the project. According to Allied Market Research company, the BIM market size was valued at over $5 billion in 2019 and is projected to reach $15 billion by 2027. The major players in the BIM market include Autodesk (US); Nemetschek (Germany); Bentley Systems (US); Trimble (US); Dassault Systèmes (France); RIB (Germany); Asite (UK); AVEVA (UK); Hexagon (Sweden); Archidata (Canada); Pöyry (Finland); Beck Technology (US); Computers and Structures (US); Robert McNeel and Associates (US); 4M Company (US); CCT International (Lebanon).

2.2.2 BIM applications in the infrastructure sector

Initially, the objective of BIM was to assist the AEC industries during the process of vertical construction, such as buildings, hospitals, schools, etc. As the popularity of BIM increased, this technology has been expanding into other domains in construction which it was not originally intended to address, including civil infrastructure (Bradley et al., 2016; Costin et al., 2018). Since BIM was originally intended to be used in the construction of vertical structures, it is believed that BIM in infrastructure is approximately three years behind from the building sector, but evidence has recently demonstrated that the use of BIM in infrastructure is increasing (Costin et al., 2018). A survey conducted by Dodge Data and Analytics (2017) reported that BIM users at a high level of implementation (on at least half of their projects) increased from 20% in 2015 to 52% in 2017, only in the transportation infrastructure sector. With the continuous advances of smart technologies, it is expected that BIM adoption will keep increasing in this sector.

BIM has numerous applications in the infrastructure sector that provide valuable improvements to the project life-cycle. Through its different applications, BIM can improve collaboration among the construction teams, reduce time and cost, and make construction operations more efficient. Some of the most common BIM applications for infrastructure projects are as follows.

Design and Coordination

Automated reviews of 3D models for clash detection are an effective and automated way of detecting design errors during the design stage of an infrastructure project. However, simple automated clash detection of 3D models usually detects irrelevant clashes and it cannot categorize these errors. Additionally, if the level of 3D geometry is too low, it will be difficult to perform an accurate clash detection using this method. Conversely, BIM provides the ability to combine clash detection with analysis based on pre-defined rules. Figure 2.5 shows an example of clash detection performed with BIM for road construction. When using BIM, clashes can be identified, categorized, and interpreted as to be relevant or irrelevant. Performing BIM-based clash detection result in an automated and highly time-effective solution that can reduce and prevent design errors that could have been costly if not detected on time (Mattsson and Rodny, 2013).

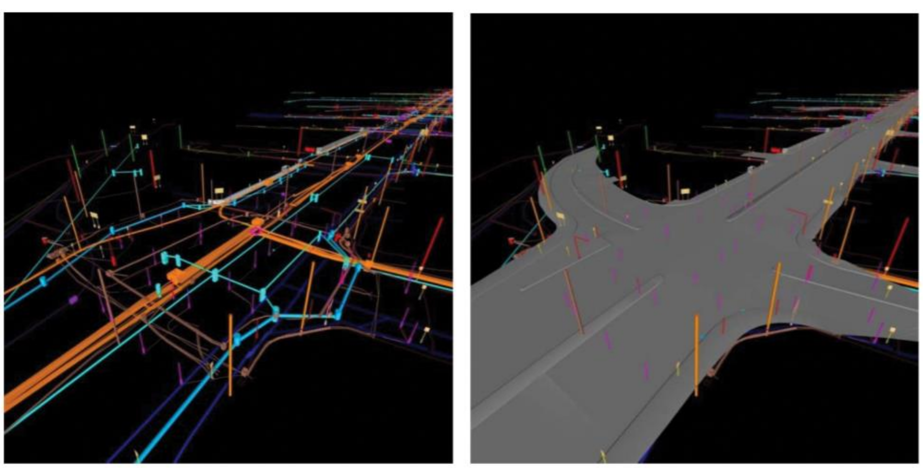

Figure 2.5 Different levels of screenshot detail in BIM from the engineering analysis and the results of clash detection (Chong et al., 2017)

<u>Control Safety</u>

Safety is a major concern in the infrastructure sector due to the frequent loss of life, injuries, and near-misses that occur during the construction or operational phase of the structure. The growing implementation of BIM in this industry is changing the way safety can be addressed for the prevention of a disaster. Through 3D visualization, BIM can be used to determine the crane's reach capabilities, as well as examine potential risks in case of load fall, or to evaluate any possible obstacles that the crane jib could hit (Ahankoob et al., 2012). BIM also provides detailed visualizations that can be used to monitor the structural performance of bridge components to prevent failures and breakdown during its operational phase (Delgado et al., 2017). Additionally, BIM systems allow for the design of roads and bridges as they “must” be built to detect failures before their physical realization, as shown in Figure 2.6, through advanced virtual simulations (Biancardo et al. 2020).

Figure 2.6 BIM simulation and modeling for mitigating physical risk and promoting safety on-site (Radley, 2017)

Design Communication

BIM improves communication among stakeholders by providing a more effective environment for collaboration compared to other traditional methods, as shown in Figure 2.7. When using BIM, different stakeholders can collaborate from anywhere in real-time on the same design through shared platforms via cloud systems. Any modifications to the project performed by any team will immediately be seen by the rest of the parties involved in the project (Erboz, 2017).

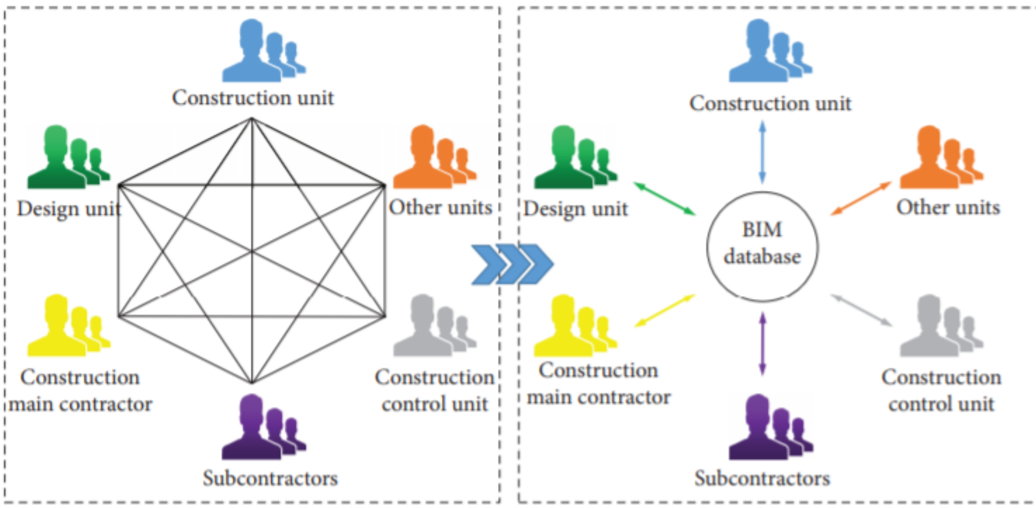

Figure 2.7 Traditional vs BIM approach for design communication (Wang et al., 2018)

Analysis and Simulation

A BIM model enables for analysis and simulations of what is planned to be constructed. Designers can incorporate BIM to determine if the design will satisfy all the requirements and the expected functions for the structure before it is built, as shown in Figure 2.8. The simulation can also determine how the structure will operate after its completion. In some cases, simulations can be performed to predict the impact of seismic events on bridges, roads, and tunnels, to assist the designer in making the appropriate modifications to generate durable designs. Furthermore, road safety simulation can ensure that the road design meets the requirements for sigh distances, taking into consideration road geometry and external obstructions (Mattsson and Rodny, 2013).

Figure 2.8 Proposed design in an existing environment for Zhengzhou-Xixia expressway project (Geospatial World, 2019)

Schedule Simulation (4D)

BIM systems can link scheduling to the 3D model, as shown in Figure 2.9. Simulated construction schedules allow BIM users to visually understand the duration and sequence of tasks in the construction process, as well as predicting potential problems that may occur during the different construction activities. Using BIM for schedule simulation reduces delays and sequencing problems (Romigh et al., 2017).

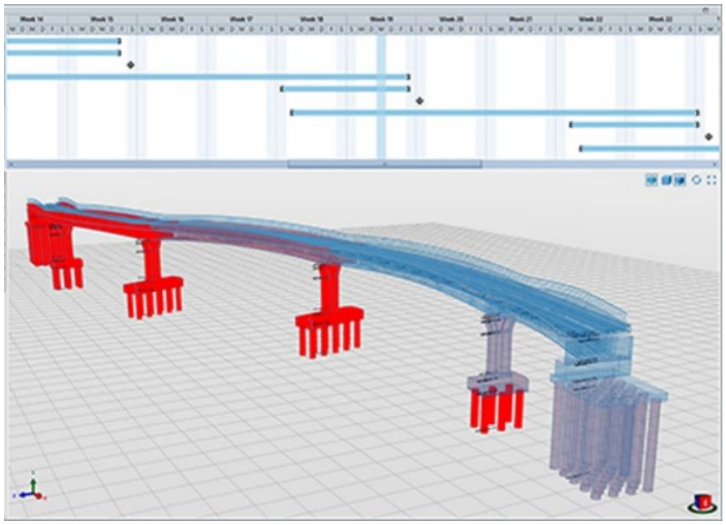

Figure 2.9 Screenshot of a 4D BIM model for a bridge construction project (ALLPLAN, 2019)

Cost Estimation (5D)

BIM generates detailed cost estimates of a project for construction companies while reducing the time and expenses needed. BIM models contain estimating data of labor cost, material cost, and equipment cost. Therefore, BIM can perform the quantity take-offs and pricing required for cost estimating (Sattineni and Bradford, 2011). During infrastructure construction, 5D BIM provides the ability to generate savings and efficiencies and to drive cost in the direction that is desired (Mitchell, 2012).

2.3 Artificial Intelligence

John McCarthy first coined the term Artificial Intelligence (AI) during a summer workshop that he organized by the name of the Dartmouth Summer Research project on Artificial Intelligence in 1956. The workshop was proposed by Marvin Lee Minsky and two senior scientists of IBM, Claude Shannon, and Nathaniel Rochester. The objective of this event was to invite a group of researchers from a variety of disciplines including language simulation, neuron nets, complexity theory, and many others to discuss what was known then as the field of AI (Marr, 2018). Minsky, who is considered one of the founding fathers of AI, defined this field as "the science of making machines do things that would require intelligence if done by men. They require high-level mental processes such as perceptual learning, memory organization, and critical reasoning" (Villani, 2018). Today, modern dictionary definitions categorize AI as a sub-field of computer science.

In the past few years, AI has evolved into a powerful tool that enables machines to simulate human behavior to perform specific tasks. The ability to "learn" in AI systems comes from the use of machine learning, which is a subset within the broad field of AI. Machine learning uses algorithms that enable a machine to learn from the data it is exposed to, without being explicitly programmed. In simpler words, the machine keeps improving as it is exposed to more data, allowing it to become better at understanding and providing insights. This approach eliminates the need to hand-code the software with a list of actions and how the machine must react with each of them (De Jesus, 2017).

One of the revolutionary approaches to process and analyze data has been deep learning and artificial neural networks. Artificial neural networks are a series of algorithms designed to imitate how the human brain works so that computers can be trained to recognize patterns from unstructured data. A neural network consists of three or more layers, namely an input layer, one or more hidden layers, and an output layer, as shown in Figure 2.10. Data ingestion occurs via the input layer, which communicates to one or more hidden layers where the data are transformed based on the weighted connections in each node. Each of the hidden layers corresponds with a different level of abstraction, where the information is passed from low-level layers to high-level layers of data abstraction. The hidden layers then link to the output layer that produces the result for given inputs. Figure 2.11 shows an example of how image recognition is achieved using artificial neural networks. The first hidden layer identifies the basic patterns such as lines, edges, and corners. Then the next ones detect larger patterns like lips and eyes, and this process keeps repeating until the description is complete. However, a typical neural network may contain thousands or even millions of processing nodes that are tightly connected (Hurwitz and Kirsch, 2018; Perez et al., 2018; Villani, 2018).

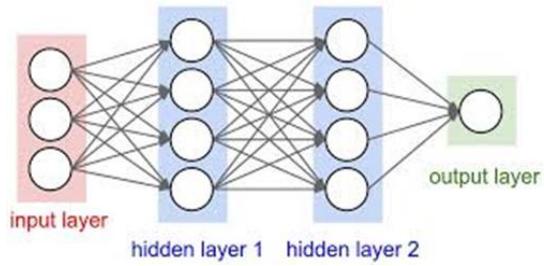

Figure 2.10 Example of a simple neural network (Rosebrock, 2016)

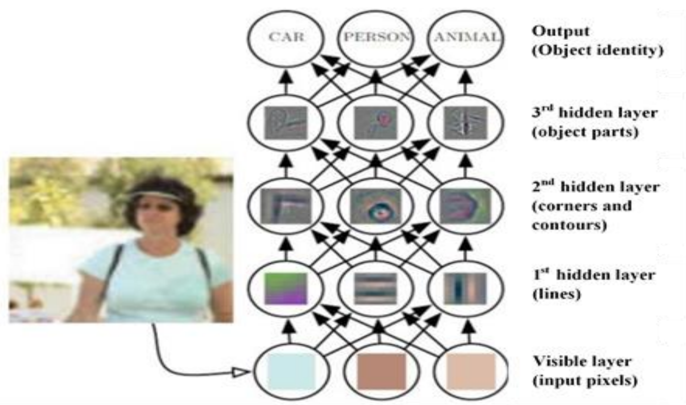

Figure 2.11 Process of neural network image recognition (Goodfellow et al., 2016)

2.3.1 The current state of AI in construction and engineering

When it comes to implementing AI solutions, engineering and construction fields are falling behind several other industries. According to the published article *Artificial intelligence: Construction technology's next frontier* by McKinsey and Company, AI use cases in construction are still relatively nascent because not many companies are willing to take the risk of implementing AI technologies. Even though the narrow set of companies that are currently using AI-focused approaches are gaining significant market traction and attention, the amount of construction companies implementing AI solutions is considerably low. Figure 2.12 shows the current adoption of AI in the construction sector compared with 12 other industries. Ten of those industries are more advanced in the current adoption of AI, and it is expected that all 12 increase spending on AI at a faster pace over the next three years.

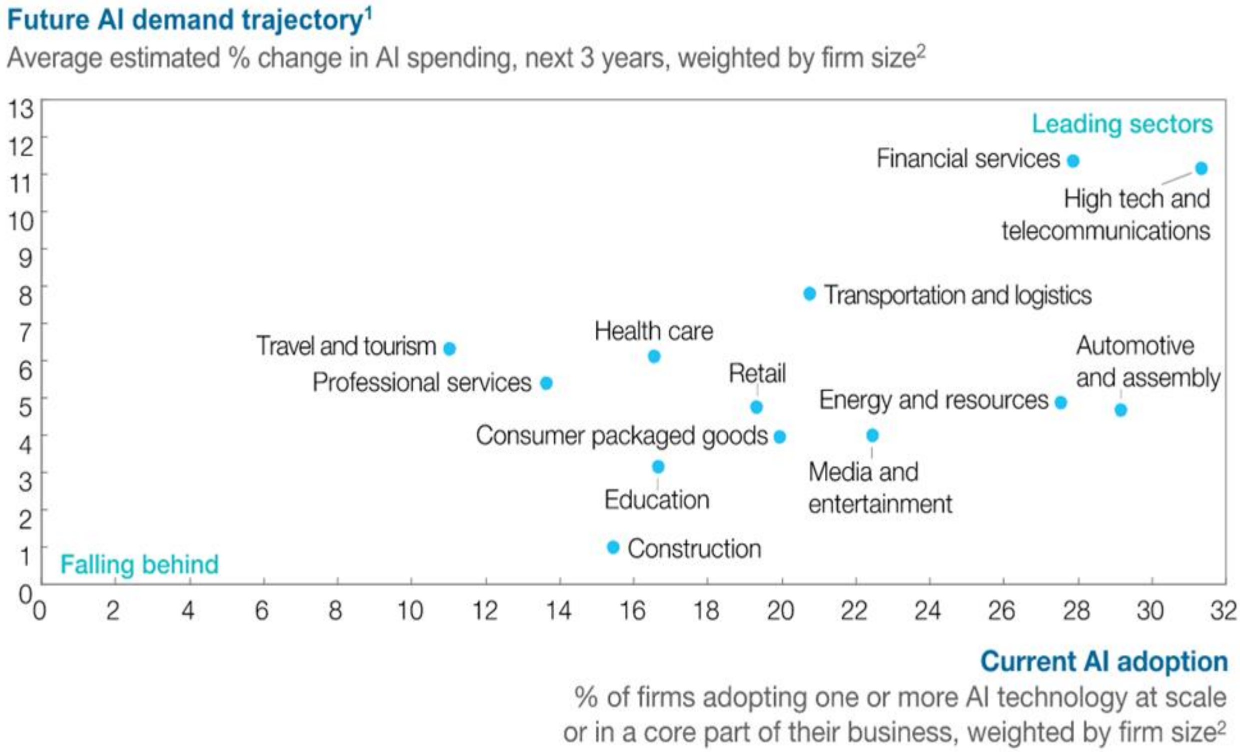

Figure 2.12 Current AI adoption vs future AI demand trajectory for various industries (Blanco et al., 2018)

2.3.2 AI applications in the infrastructure sector

The potential benefits of AI and machine learning in the construction sector are immense due to the tremendous advantages it provides. Even though the adoption of this technology is higher in other industries, construction companies are slowly starting to implement AI for the improvement of construction operations and reduction of project costs. Some examples of AI use in the infrastructure construction sector include the following:

<u>Autonomous Construction Equipment</u>

The rapid advancement in technology is taking construction equipment to the next level. In recent years, several companies have been working on the development of fully autonomous construction machinery to perform construction tasks without any human intervention. Although complete autonomy of these machinery has not been entirely achieved, numerous construction equipment companies have been able to retrofit AI guidance systems into existing construction equipment, such as bulldozers and excavators, to perform excavating and grading operations in a semi-automatic manner, which means that human involvement is still needed to assist with safe operation. One example is the semi-automatic bulldozer, which is operated by humans, but it automatically collects terrain data while moving around a site. The bulldozer then utilizes the data to decide how to handle materials or accomplish different tasks. By analyzing the data, the machine can learn whether to spread or fill materials. The bulldozer will also be able to store information about the surrounding area and use it when returning to a site later to perform additional work (Welles, 2020).

Drones

The drone industry is being revolutionized with the incorporation of computer vision technologies supported by machine learning and deep learning algorithms, which enable the development of self-flying drones. Autonomous flying machines, or drones, are now being integrated with computer vision technology that uses artificial neural networks to detect objects, such as vehicles, foothills, buildings, and threes. Object tracking drones can capture real-time data during the flight, process it instantly with an onboard processing system, and make human-independent decisions based on the processed data. Some useful applications of computer vision in drones include object tracking, self-navigation, and obstacle detection, and collision avoidance (Bisen, 2020). Currently, drones are being utilized for surveying operations and capturing overhead images that provide a better view of the site to track construction progress. Additionally, video cameras or drones integrated with computer vision technology can monitor the actions of workers and heavy equipment, and the location of the material as shown in Figure 2.13.

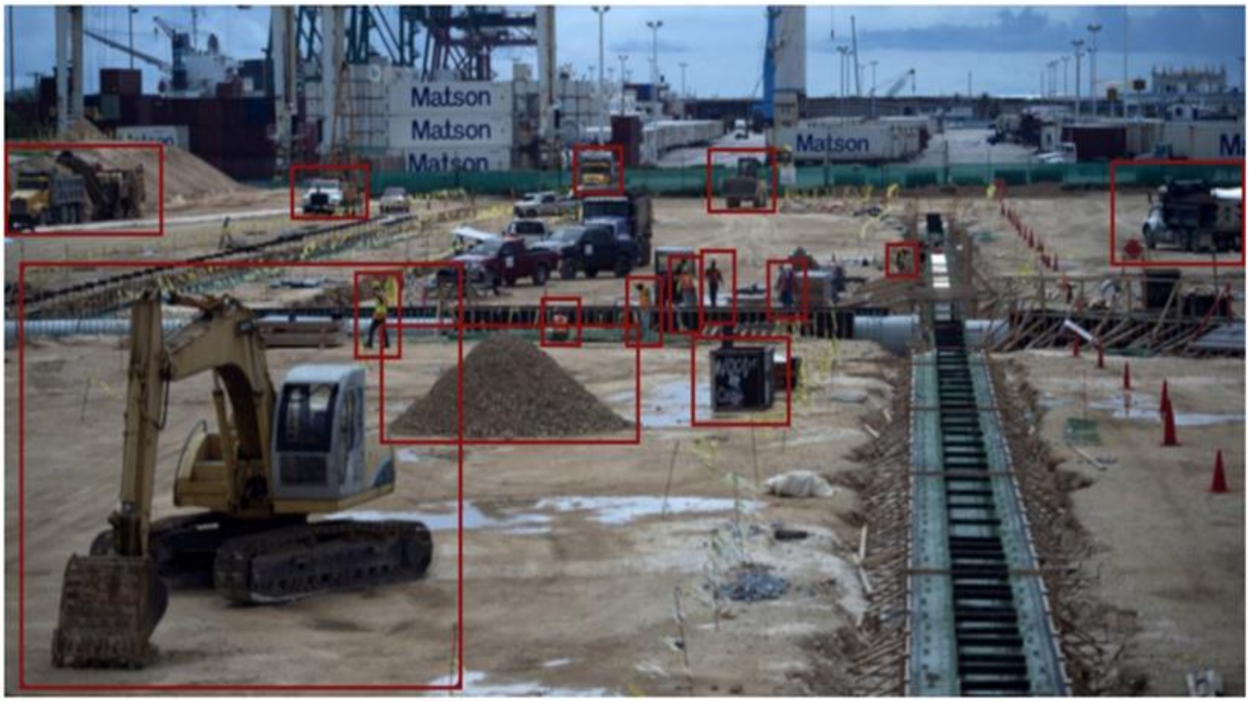

Figure 2.13 Drone using AI techniques to monitor actions at the construction site (Schütte, 2019)

Robotics

Robotics is an important area of AI since machine learning techniques are utilized to give robots their ability to perform different tasks. The infrastructure construction industry is working toward the development of different robots to perform different tasks throughout the various phases of a project. One of the most famous robots in the construction sector these days is TyBot used mainly in the construction of bridges. TyBot is an autonomous rebar-tying robot that uses a series of cameras and AI to identify the intersection of rebars without the need for an operator or pre-programming. This machine is capable of performing 1,000 ties per hour, which is approximately the equivalent of a six to eight worker crew. Additionally, the development of another robot that will complement TyBot is in the process and will be called IronBot. This new robot will be able to carry and place rebar based on preset plans (Rubenstone, 2019).

Road Condition Assessment

RoadBotics is an infrastructure technology company that uses smartphone cameras to scan pavements from a vehicle in motion and then feeds the data into computer vision algorithms to detect any existing defects on the road. Subsequently, the system uses this information to create pavement condition maps. This technology can diagnose road defects more accurately and effectively than a human inspector can and collects data at a low cost. The level of precision that RoadBotics systems can achieve using a smartphone camera is sufficient to notify agencies if maintenance operations are required. The camera can identify defects such as transverse and longitudinal cracking, patches and sealant, surface deterioration, potholes, surface distortions, and fatigue cracking. The detection of these defects allows users to minimize costs by performing maintenance operations on time before the road becomes severely damaged and irreparable (Fong et al., 2018).

The system relies on several years of research and data collection. Expert staff has trained a series of neural networks to identify different features on a labeled video of roads and consistently classifies data into five categories as depicted in Figure 2.14. The RoadBotics system is also combined with the GPS information collected by the modified smartphone to produce a heat map of a city's road as shown in Figure 2.15 (Fong et al., 2018).

Figure 2.14 RoadBotic's Ratings for road conditions (RoadBotics, 2020)

Figure 2.15 Road network conditions displayed on the RoadBotic's online asset management platform, Roadway (RoadBotics, 2020)

2.4 Internet of Things

The Internet of Things (IoT) concept was coined in 1999 by a member of the Radio Frequency Identification (RFID) community development, but it has recently become more relevant to the practical world due to the growth of mobile devices, embedded ubiquitous communication, cloud computing, and data analytics (Arslan et al., 2019). IoT tools are the technological components that enable objects to connect via the internet, enabling them to collect or share data. These may include mobile devices, sensors, 3D scanners, cameras, and more (Nagy et al., 2018).

Similar to other innovative technologies, IoT tools are underutilized in the construction sector. However, evidence shows that research efforts are expanding regarding the implementation of IoT technologies in smart buildings, communities, cities, and infrastructure. Additionally, several researchers have tried to utilize IoT to overcome health and safety problems on the construction job site. Other researchers have concentrated on IoT technology for a better project or construction management performance (Arslan et al., 2019).

IoT tools are crucial components for other major technologies such as BIM and AI. Most importantly, IoT-connected devices are one of the many technologies that make the creation of a DT possible. During a DT application, dynamic or operational data can be obtained, using the IoT and sensors, and displayed in real (or near-real) time through one-directional flow from the physical to the digital asset. In the case of a transport asset, the data can be analyzed to inform and predict the behavior of the civil structure. The output and results fed back and updated into the organizations existing systems can then be used to facilitate decision-making (EIT, 2019).

2.5 Smart Sensors

A smart sensor is the combination of a sensing element with processing capabilities provided by a microprocessor. In other words, smart sensors are basic sensing elements with embedded intelligence which process the data and provide an informative output to an external user. Additionally, these sensors have the capabilities to monitor themselves and respond to changing conditions optimizing safety and performance (Hunter et al., 2012).

In the infrastructure sector, smart sensors are embedded systems that capture information about the civil structure condition. Figure 2.16 shows different types of sensors, and their functions, that can be installed in a bridge to monitor distinct parameters of the structure. Unlike traditional sensors, smart sensors enable real-time continuous monitoring and enhanced capabilities regarding the interconnectivity with other sensing systems, providing high-quality data in the central control systems. Smart sensors used for intelligent construction are characterized by advanced architectures, extended battery life, and minimized size. These sensors are capable of detecting simultaneously parameters that pertain to the health of the asset for timely and proactive decision-making (Michalis, 2019).

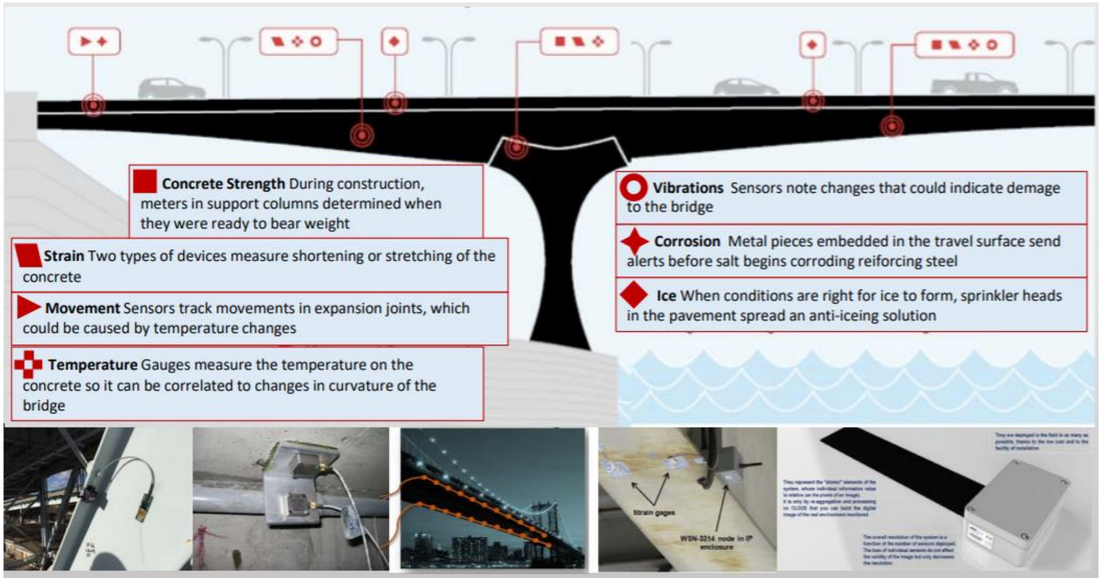

Figure 2.16 Smart sensors and their functions (Zagari, 2018)

2.6 Digital Twins

The use of "twins" is becoming popular in a wide variety of field industries during recent years. However, the concept of using digital twins (DT) can be traced back to NASA's Apollo program (Rosen et al., 2015). NASA built at least two identical spacecraft, where one of them was left on earth and referred to as a twin. The purpose of the twin was to reflect the status and condition of the space vehicle on the mission. The twin was extensively utilized for training during flight preparation in the early stages of the project. During the flight mission, the twin was used to simulate possible solutions on the earth-based model, where the available flight data were integrated to create the representative conditions of the space vehicle at a high level of precision, and thus assist the astronauts in orbit to make better decisions in critical situations.

In 2002, Michael Grieves introduced the concept of virtual digital representations equivalent to physical products at the University of Michigan, Executive Course on Product Lifecycle Management (PLM). Although the concept introduced by Grieves was not known as a DT at that time (it was referred to as "Mirrored Spaced Model" from 2003 to 2006, and

"Information Mirroring Model" from 2006 to 2010 [Wang, 2020]), its conceptual model, as shown in Figure 2.17, had all the elements of a DT: the real space, the virtual space, the link for data flow from real space to virtual space, and the link for information flow from virtual space to real space (Grieves and Vickers, 2016). In 2011, Grieves wrote his book Virtually Perfect: *Driving Innovative and Lean Products through Product Lifecycle Management* where the concept was still referred to as Information Mirroring Model, but the term "digital twin" was used by his co-author John Vickers as a noun to describe their model. From that point on, the phrase "digital twin" has been adopted when referring to the conceptual model.

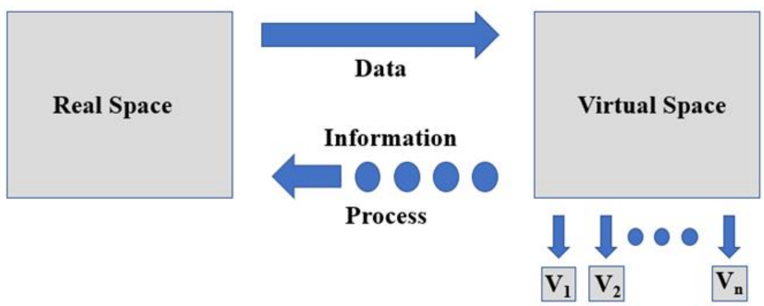

Figure 2.17 Grieves' conceptual model containing elements of a DT model (adapted from Grieves and Vickers, 2016)

The term digital twin (DT) is frequently being used in all industry sectors as the world becomes more digitalized. However, there is still much misunderstanding and confusion around what DT is and what are its potential applications. Table 2.1 presents DT definitions across the industry and academia. Definitions of DT tend to slightly differ according to the interest of the researcher or business involved. While the characteristics are relatively consistent, the stated purposes of DT can vary significantly (Gerber et al., 2019). For this research, the IBM (2020) definition will be followed, which states that a DT is a "virtual representation of an object or system that spans its lifecycle, is updated from real-time data, and uses simulation, machine learning, and reasoning to help decision-making."

The DT and its ecosystems typically vary in scale and complexity with respect to size and scope. The size determines the level of detail and accuracy of the model. The scope is the section of the real-world that the model considers, whether if it's a car engine or a megastructure (Gerber et al., 2019). As shown in Figure 2.18, a DT is composed of other major innovative technologies, including BIM and AI through machine learning.

Table 2.1 Definitions of a DT from industry and academia

Source	Definition
NASA (2012)	"A DT is an integrated Multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin
Michael Grieves (2016)	"The DT is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro (atomic level) to the macro (geometrical level). At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its DT."
Deloitte (2017)	"A DT is a near-real-time digital image of a physical object or process that helps optimize business performance."
Microsoft (2017)	"A DT is a virtual model of a process, product, production asset, or service. Sensor-enabled and IoT-connected machines and devices, combined with machine learning and advanced analytics can be used to view the device's state in real-time. When combined with both 2D and 3D design information, a DT can visualize the physical world and provide a method to simulate electronic, mechanical, and combined system outcomes."
IBM (2019)	"A DT is a virtual representation of a physical object or system across its lifecycle, using real-time data to enable understanding, learning, and reasoning."
Gerber et al., ARUP (2019)	"A DT is the combination of a computational model and a real-world system, designed to monitor, control, and optimize its functionality. Through data and feedback, both simulated and real, a DT can develop capacities for autonomy and to learn from and reason about its environment."
Digital Twin Consortium (2020)	"A DT is a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity."
Deloitte (2020)	"A DT is a digital simulation of physical systems, assets, or processes. Often paired with IoT technology to instrument simulated systems, DT technologies are supported by data science and machine learning, and supply optimizations and insights for physical world action."

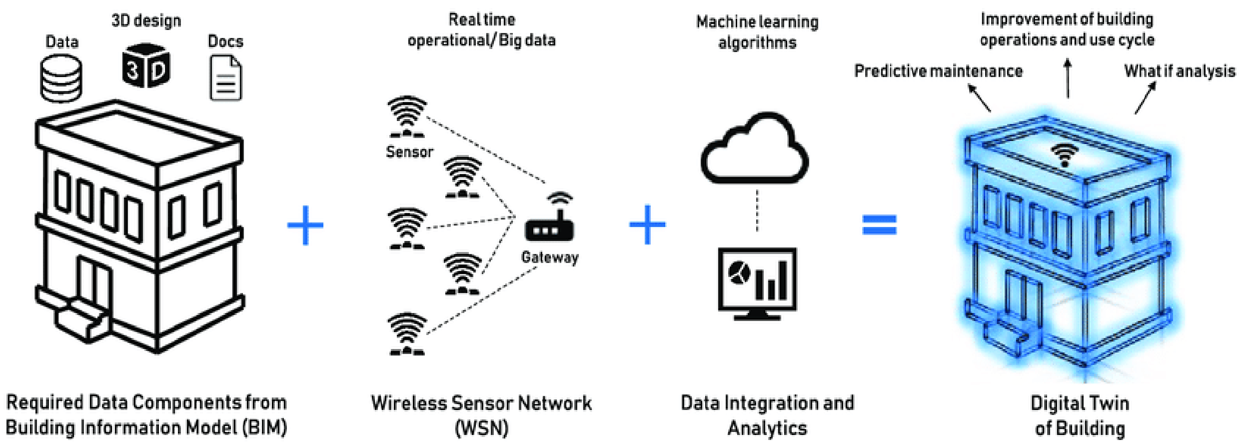

Figure 2.18 Essential components to create a DT (Khajav et al., 2019)

2.6.1 DT technology in the infrastructure sector

Today, numerous companies across multiple disciplines are using DT capabilities in a variety of ways. In the automotive and aircraft sector, this technology is utilized for optimizing the entire manufacturing value chains and innovating new products. In healthcare, DT systems can be created to accurately simulate a human heart for clinical diagnoses, education, and training (Briggs et al., 2020). The infrastructure sector is now also trying to make use of this innovative technology. DT technology promises more effective asset design, project execution, and asset operations. By integrating data and information in real-time throughout the transport system lifecycle, the technology can offer short and long-term efficiency and productivity improvements. Unlike BIM or a 3D model, a DT is a data resource that can optimize the design of new assets, monitor existing asset conditions, verify the as-built situation, run 'what if' simulations and scenarios, or provide a digital snapshot for future works. As a result, DT technology has the potential to drastically eliminate errors that could result from using more traditional methods (IET, 2019). Table 2.2 presents the main benefits that adopting a DT approach can bring to the construction industry.

Table 2.2 Main benefits of DT technologies for construction projects (adapted from IET, 2019)

Reduce construction and operating costs	Virtual scenarios on construction sequencing and logistics can be run and visualized, familiarizing workers with required tasks and reducing costly re-works. Through data-driven decision-making, and AI/ML, they can predict maintenance activities and events, which in turn will help navigate unexpected interventions and ultimately streamline costs throughout the asset's operational life.
Increase productivity and collaboration	Vital information about the asset can be stored and analyzed throughout its lifecycle and kept current. This information (such as design documentation, inventories, material specifications, and schedules) can be easily accessed and used to assist decision-making and de-risk project execution.
Improve safety	On-site workers can get real-time tracking and alerts about the site, including hazardous area notifications and emergency situation response instructions
Optimize asset performance	Operational and occupational data can be monitored and analyzed in real-time, providing valuable insights on how the asset is used and currently performing.

Any large change to an industry requires overcoming technical, legal, and cultural hurdles. This is the case with emerging technologies like the DT. Although DT technologies are becoming more popular in the construction industry in general, there is no significant evidence in the literature proving that DT systems are being implemented at a full scale with a life-cycle perspective of infrastructure megaprojects. Much work is still needed to promote and encourage the industry stakeholders to utilize this technology in future infrastructure projects. New skills and talent must be developed, new training must be created, and cultures must change (Gerber et al., 2019). Ultimately, the evolution of DT technologies will help government agencies, private companies, and anyone in the infrastructure sector to make more informed decisions, through real-time data solutions.

CHAPTER 3: DIGITAL TWIN SURVEY OF INDUSTRY PROFESSIONALS

3.1 Methodology

Key tasks involved in this study were to 1) establish the target groups for the survey; 2) design the survey questions and layout; 3) distribute the survey among the industry professionals; and 4) perform data analysis. The first step was to identify the specific group of professionals to complete the survey. For this research, any professional involved in the infrastructure sector could participate in the survey. However, the survey contained a filter question asking the participants about their experience with BIM since BIM is a crucial component of a DT. The questionnaire was terminated for those participants who indicated that they had no experience using BIM.

QuestionproTM was used to conduct the survey due to its simplicity, user-friendliness, and analytical tools that it provides. The survey was distributed via email among the members of the Transportation Research Board (TRB) Committee on Pavement Condition Evaluation, the International Society for Intelligent Construction (ISIC) North America chapter, the Highway Engineering Exchange Program (HEEP), and also posted on multiple LinkedIn groups. Data were collected over one month.

The questionnaire was divided into two sections; the first half included basic company-related questions (four) while the second half consisted of BIM and DT-related questions (six). Both sections contained a combination of multiple-choice and open-ended questions. The analysis was performed using the analytical features available in Questionpro. The survey questionnaire is provided in the appendix.

3.2 Survey Part 1: Company-related questions

3.2.1 Type of service

Out of 102 participants who accessed the survey online, 49 participants completed the survey. As shown in Figure 3.1, 14 industry professionals (29%) indicated that their company focused on project design, six (12%) stated that their company concentrated on project management process, and only one (2%) reported that the company performed construction activities. Also, of the 49 industry professionals, 28 (57%) participants selected the option of "other types of services" that included mostly employment by the Departments of Transportation (DOT) or government agencies (7), all of the above (7), construction equipment manufacturers (5), machine automation or machine guidance providers (2), higher education (2), asphalt producers and suppliers (1) dealer for intelligence pavement technology (1) material and construction inspection (1) pavement maintenance (1), and electronic components manufacturer (1). This information shows the variety of industry professionals who participated in the survey and the different activities that each company performs.

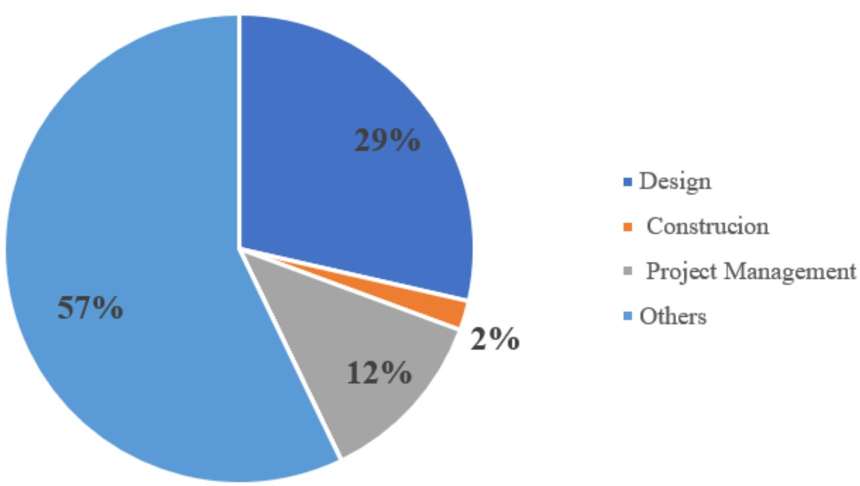

Figure 3.1 Type of service that the participant's company provides

3.2.2 Number of employees

As shown in Figure 3.2, of the 49 industry professionals, 28 (57%) reported that their company had more than 500 employees, and 12 (25%) mentioned that the number of employees working in their company was between 50 and 500. The remaining nine participants (18%) indicated that less than 50 employees worked in their company.

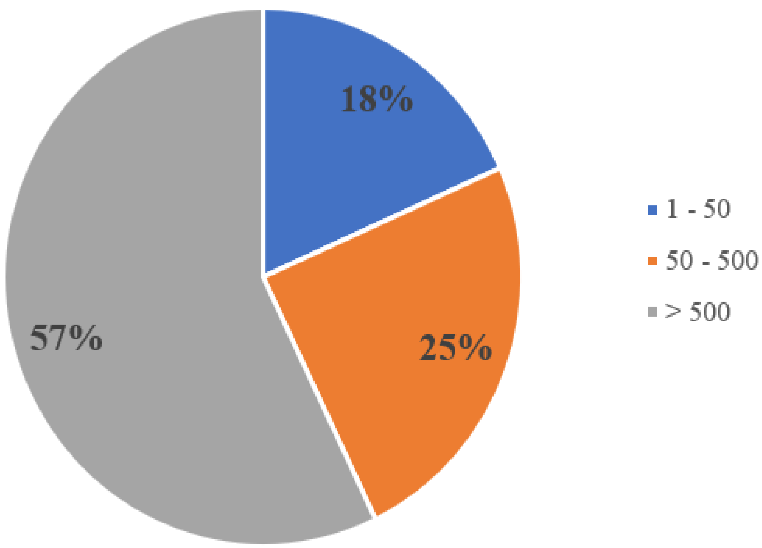

Figure 3.2 Number of employees working in the company

3.2.3 Participant's role in their company

As shown in Table 3.1, the largest groups of industry professionals that responded to the survey were CADD engineers, general managers, product managers, and accredited professionals, with five participants from each group. Overall, a diverse group of industry professionals participated, allowing the results to be more representative of the infrastructure sector as a whole.

Table 3.1 Reported role of industry professionals in their companies

Role of professionals in their companies	#	Role of professionals in their Companies	#
CADD Engineer	5	Professor in Transportation Engineering	1
General Manager	5	Design Services Manager	1
Product Manager	5	Technical Assistant to Design and Construction Staff	1
Accredited Professional (AP)	5	Equipment Manufacturer for Road Construction	1
Principal Engineer	4	Sales Representative	1
Paving Application and Technology Specialist	4	Field Engineer	1
Researcher	4	Technology Implementation Manager	1
Pavement Engineer	3	Pavement Performance Analyst	1
Standards and Design Engineer	2	Traffic Engineer	1
BIM Manager	2	Executive Director	1

3.2.4 Experience using BIM technologies

As shown in Figure 3.3, one-third (18, 37%) of the participants reported that they had no experience using BIM, while another one-third (17, 35%) indicated that they had implemented BIM for more than five years. The remaining one-third replied that they adopted BIM technologies three to four years ago (eight, 16%), one to two years ago (five, 10%), and less than a year ago (one, 2%). This "filter question" was meant to help respondents avoid answering the follow-up questions on DT. The survey ended for professionals who mentioned that their company has no experience using BIM systems.

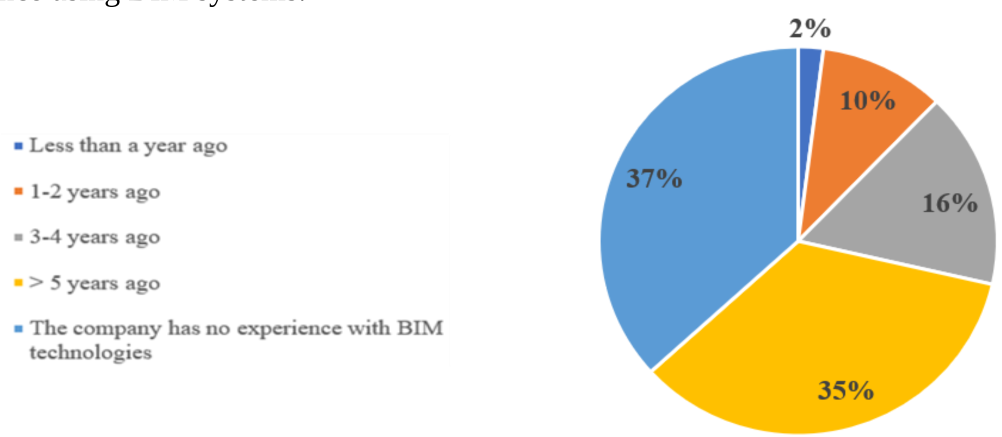

Figure 3.3 Number of years since company started using BIM

3.3 Survey Part 2: BIM and DT-related questions

3.3.1 Evaluation of BIM experience

Only industry professionals with BIM experience participated in this section (a total of 23 respondents). The industry professionals were asked to evaluate their experience with BIM when implemented for infrastructure projects. Figure 3.4 shows that 11 (48%) participants considered that their experience with BIM was good, while six (26%) stated that their experience with that technology was fair. Nine professionals (22%) reported that working with BIM was excellent, and only one respondent (4%) had a negative experience using BIM.

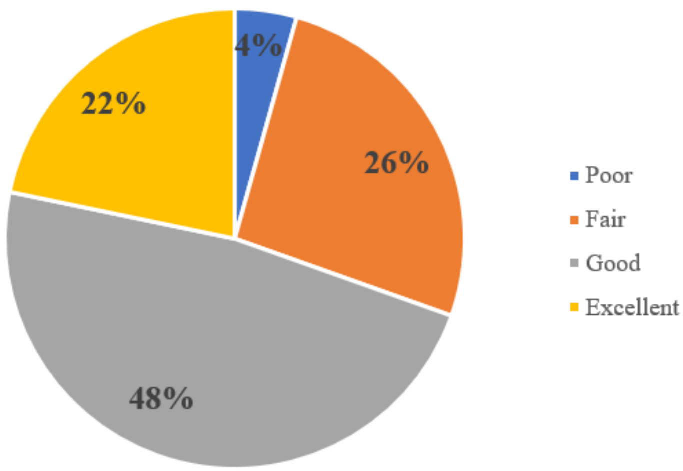

Figure 3.4 Participant's evaluation of their experience with BIM

The industry professionals then provided comments to justify their response about their BIM experience being excellent, good, fair, or poor. The results showed significant patterns in the remarks provided by the respondents. For example, all professionals that answered "excellent" to the question mentioned that they had been utilizing BIM technologies for more than five years and were incorporating the use of mobile communication technology and other innovative tools for field activities. They also recognized that the technology was in the future for transportation asset construction. Similarly, a majority of industry professionals who responded "good" to the question shared a similar opinion. Many of them reported the numerous benefits that BIM could bring to a project. They also described challenges such as the lack of BIM standards for the transportation industry and the complex cultural shifts that are preventing companies from adopting the technology. Industry professionals who answered "fair" to the question mentioned that BIM was still a work in progress in their companies that needed some improvements, mainly related to data management.

3.3.2 Level of familiarity with the DT concept

Based on the responses, 11 (48%) industry professionals were familiar with the DT concept and understood how it differed from BIM. Only two (9%) were unfamiliar with this technology, and three (13%) have doubts about the theory and the purpose of DT systems (Figure 3.5).

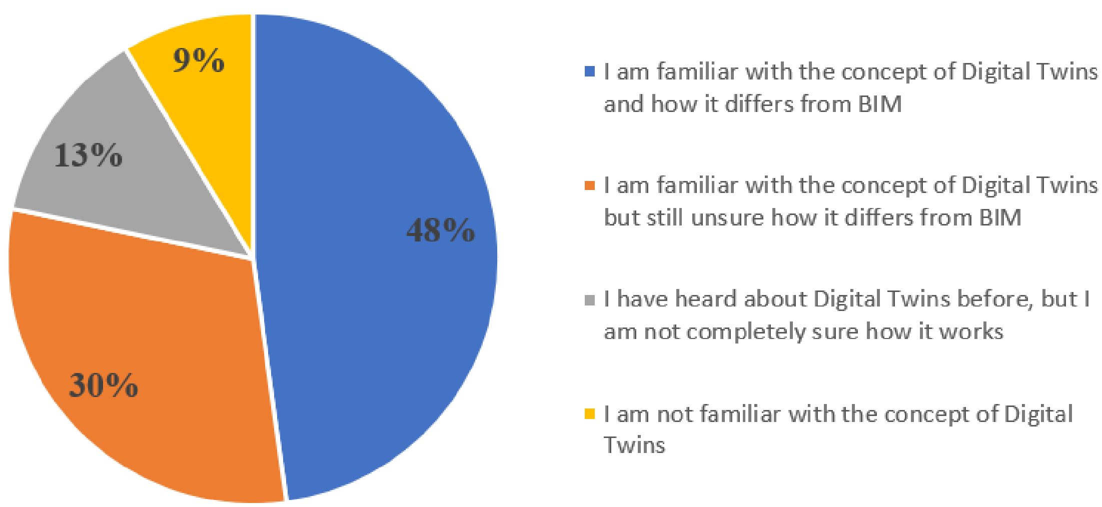

Figure 3.5 Participant's familiarity with the DT concept

3.3.3 Consideration of implementing DT technologies for future projects.

As shown in Figure 3.6, seven participants (30%) reported that they were in the process of developing a DT system, and six (26%) planned on adopting that tool one or two years from now. Another 6 (26%) expected to be utilizing twin models three years from now, and four companies (17%) had no intentions of incorporating DT technologies anytime soon.

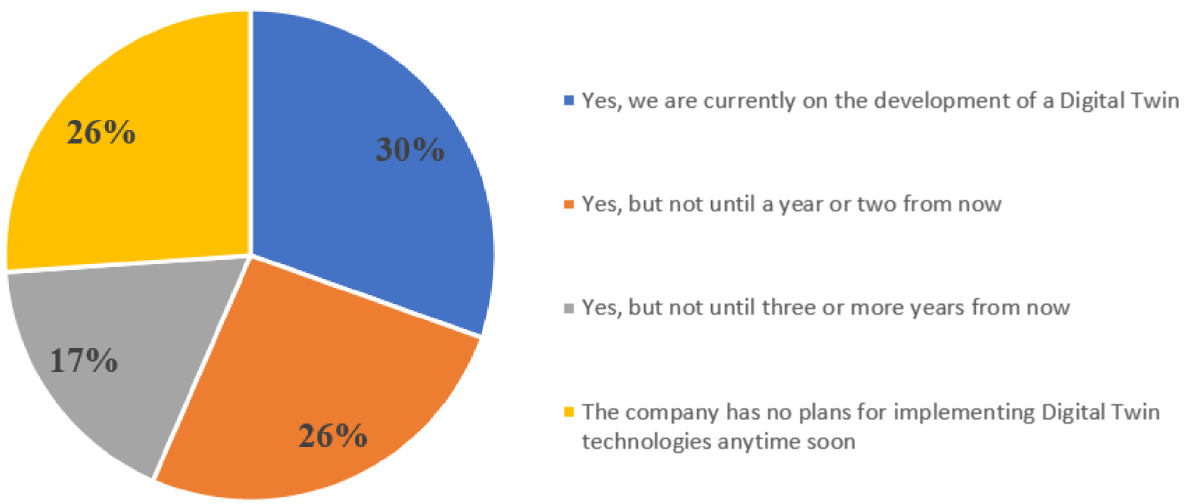

Figure 3.6 Participant's company consideration of implementing DT technology for future projects

3.3.4 Expected benefits from DT technologies.

Industry professionals indicated the top three benefits they would expect from a DT. Figure 3.7 shows that the three most selected benefits involve; 1) reduced construction and operating costs (12), 2) improved multiparty communication (12), 3) reduced in-field coordination conflicts and changes during construction (11). The results indicated that infrastructure companies are more interested in the reduction of the overall cost of a project and improved communication and coordination among the teams working on the project.

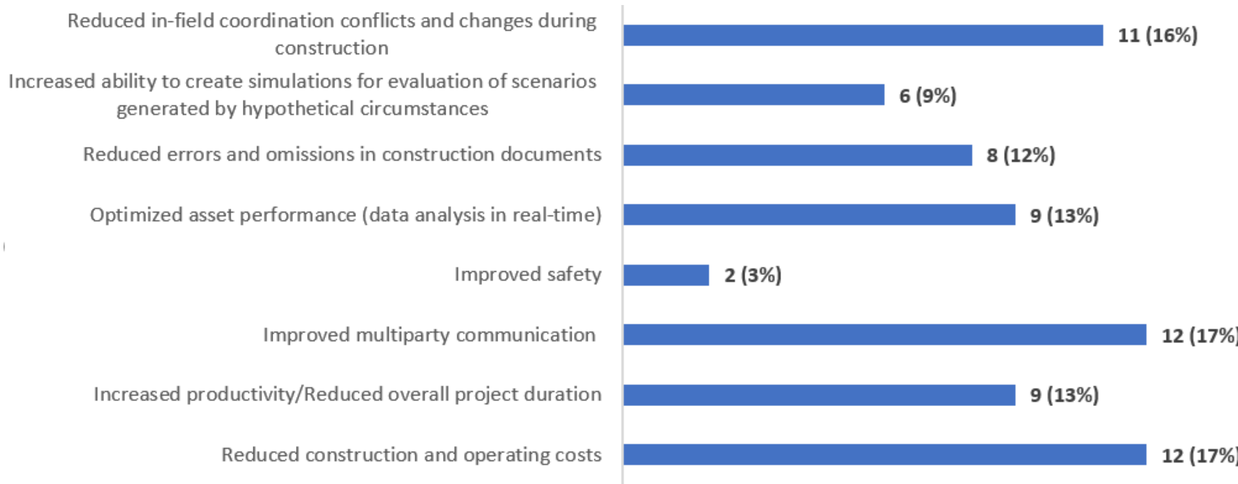

Figure 3.7 Participant's expected benefits from DT technologies

3.3.5 Predicted level of DT implementation

The respondents were asked to predict the level of DT implementation in which their company will be five years from now. The levels presented in this question were adopted from a study conducted by Gerber et al. and are described in Table 3.2. As shown in Figure 3.8, a high percentage of industry professionals (30%) believed that their company would be using a digital model with some capacity for feedback and control, but some data would still be analyzed by a human operator (level 2). Five industry professionals (22%) responded that they did not see their company using that technology even five years from now. This information shows that different companies and agencies have distinct opinions about the DT; while some respondents believe in the potential of this technology and want to make the most out of it, others simply prefer not to adopt this technology at all.

Table 3.2 Levels of DT implementation (adapted from Gerber et al., 2019)

Level of DT implementation	Description
Level 1	Using a digital model linked to the physical asset in real-time but lacking intelligence, learning, or autonomy.
Level 2	Using a digital model with some capacity for feedback and control, but some data still analyzed by a human operator.
Level 3	Using a digital model able to provide predictive maintenance, analytics, and insights.
Level 4	Using a digital model with the capacity to learn efficiently from various sources of data, including the surrounding environment. The model will have the ability to autonomously learn from data and suggest solutions.

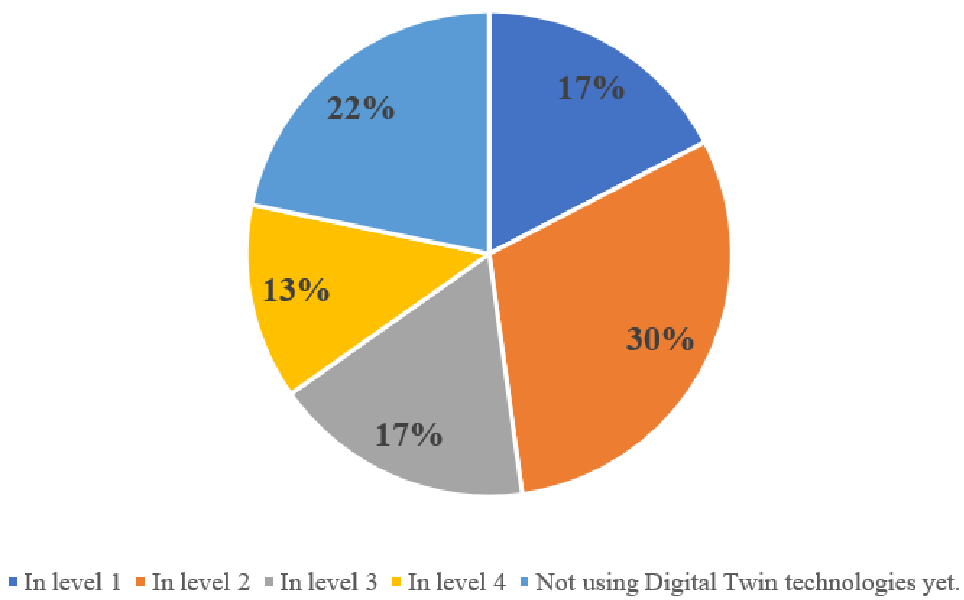

Figure 3.8 Predicted level of DT implementation in which the company will be five years from now

3.3.6 Potential challenges for the deployment of DT technologies in the infrastructure sector

To conclude the survey, the industry professionals were asked to comment about any potential challenges for the development and implementation of DT technologies in the transportation infrastructure sector. Some of the potential challenges described by industry professionals include lack of resources, lack of data standards, lack of time to learn new things, lack of trained personnel, software interoperability, limited experience, software complexity, resistance to change, cost of DT systems, and government agencies’ slow pace to adopt emerging technologies. Overall, the most common challenges reported in this survey appear to be the lack of a mature general data exchange file format and the need for qualified personnel to work with the DT.

CHAPTER 4: CONCLUSIONS AND FUTURE WORKS

4.1 Conclusions

This study provided an overview of the digital twin (DT) concept and briefly discussed its application and benefits for transportation asset construction. The current state of DT implementation in the infrastructure sector was investigated via a survey questionnaire and the collected data were analyzed. Based on the results obtained from the survey, the following conclusions can be drawn:

- There is still a significant number of companies in the infrastructure sector that have not even started implementing BIM in their projects that is a crucial component of a DT.
- There is still some confusion in the industry about how a DT is different from a BIM system.
- Although some companies are considering adopting DT solutions for future projects, there are still many with no intentions of deploying DT systems for their transport projects anytime soon.
- Infrastructure companies are more interested in the reduction of the overall cost of a project and improved communication and coordination.
- Numerous challenges remain and need to be addressed for the deployment of DT systems in the infrastructure sector. These challenges include but are not limited to lack of data standards, lack of time to learn new things, lack of trained personnel, lack of a mature general data exchange file format, resistance to cultural change, and the cost of the software and hardware needed to create and maintain a DT.

The survey shows that even though there has been some progress in the adoption of DT solutions, there is still much work to be done to fully integrate this technology in the infrastructure sector. The overall success of DT implementation will only come through collaboration among the government, industry, academia, and society. This collaboration will facilitate the process of industry standardization and consequently simplify the adoption of DT technologies. One recent example is the case of Bentley Systems, which is currently investing in a collaborative research network with academic and corporate strategic partners, to continue exploring the art of the possible DT technologies (Gerber et al., 2019). This type of partnership and relationships will help to address the technological, cultural, and societal challenges of DT, resulting in a more efficient transition to a more digitalized industry.

4.2 Future Works

The research will be expanded in the future through the collection of responses at a larger scale with a broader timeline that will be helpful to start a more informed discussion related to challenges and opportunities for DT adoption in the transportation infrastructure projects. Also, existing case studies will be collected for individual processes/methods/components and possible full-scale integration will be discussed.

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APPENDIX

Digital Twin Survey of Industry Professionals

Part 1: Company-related Questions

1 Which type of service does your company provide?

- Design
- Construction
- Project Management
- Other, please specify

2 Please select the number of employees working in your company.

- 1 – 50
- 50 – 500
- > 500

3 What is your role in this company? Please describe below.

____

4 When did your company start using BIM technologies?

- Less than a year ago
- 1 – 2 years ago
- 3 – 4 years ago
- > 5 years ago
- The company has no experience with BIM technologies

Part 2: BIM and Digital Twins-related Questions

5 Please evaluate your experience with BIM.

- Poor
- Fair
- Good
- Excellent

Please explain why ____

6 Are you familiar with the concept of Digital Twins? Do you know how Digital Twin technologies differ from BIM technologies?

- I am familiar with the concept of Digital Twins and how it differs from BIM
- I am familiar with the concept of Digital Twins but still unsure how it differs from BIM
- I have heard about Digital Twins before, but I am not completely sure how it works
- I am not familiar with the concept of Digital Twins

7 Has your company considered implementing Digital Twin technologies in any of their projects?

- Yes, we are currently on the development of a Digital Twin
- Yes, but not until a year or two from now
- Yes, but not until three or more years from now
- The company has no plans for implementing Digital Twin technologies anytime soon

8 Please select the top three benefits that you would expect from a Digital Twin.

- ☐ Reduced construction and operating costs
- ☐ Increased productivity/Reduced overall project duration
- ☐ Improved multiparty communication
- ☐ Improved safety
- ☐ Optimized asset performance (data analysis in real-time)
- ☐ Reduced errors and omissions in construction documents
- ☐ Increased ability to create simulations for evaluation of scenarios generated by hypothetical circumstances
- ☐ Reduced in-field coordination conflicts and changes during construction

9 At what level of Digital Twin do you predict your company to be five years from now?

- In level 1. Using a digital model linked to the physical asset in real-time but lacking intelligence, learning, or autonomy.
- In level 2. Using a digital model with some capacity for feedback and control, but some data still analyzed by a human operator.

- In level 3. Using a digital model able to provide predictive maintenance, analytics, and insights.
- In level 4. Using a digital model with the capacity to learn efficiently from various sources of data, including the surrounding environment. The model will have the ability to autonomously learn from data and suggest solutions.
- Not using Digital Twin technologies yet

10 Based on your experience using BIM, what potential challenges could be encountered for the development and implementation of Digital Twins in the Infrastructure sector? Please describe below.

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End of the Survey

CURRICULUM VITA

Hector Cruz was born in Mexico but immigrated to the United States in 2010. During his first years living in El Paso, Texas, he completed his high school studies in 2015. In December 2019, he earned his Bachelor of Science in Civil Engineering from the University of Texas at El Paso (UTEP). Hector worked as an undergraduate research assistant in the Center for Transportation Infrastructure Systems (CTIS) for the Tx-6949 project funded by the Texas Department of Transportation. Mr. Cruz completed his Master of Science degree in Civil Engineering in May 2021. Throughout his educational career, he has been honored to receive the prestigious Hazen and Sawyer scholarship due to outstanding academic performance, and the Patricia and Jonathan Rogers where he was selected out of a group of brilliant students based on a 500-word essay about his research study. He also had the opportunity of contributing to the publicized paper “Laboratory Investigation of The Cyclic Behavior of Cementitiously Stabilized Granular Materials Using Dissipated Strain Energy Method”, this being his first publication as a co-author. Additionally, he has been an attendee of the past two Transportation Research Board conferences organized by the Federal Highway Administration (FHWA). This is a very recognized conference in the transportation industry where he had the opportunity to interact with other professionals in this area of study and learn from presentations prepared by students from universities across the country.

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This thesis was typed by Hector Cruz.