



# Digital Twin: From Concept to Practice

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**Abstract:** Recent technological developments and advances in artificial intelligence (AI) have enabled sophisticated capabilities to be a part of digital twins (DTs), virtually making it possible to introduce automation into all aspects of work processes. Given these possibilities that DT can offer, practitioners are facing increasingly difficult decisions regarding what capabilities to select when deploying a DT in practice. The lack of research in this field has not helped. It has resulted in the rebranding and reuse of emerging technological capabilities such as prediction, simulation, AI, and machine learning (ML) as necessary constituents of DT. Inappropriate selection of capabilities in a DT can result in missed opportunities, strategic misalignments, inflated expectations, and the risk of it being rejected as hype by the practitioners. To alleviate this challenge, this paper proposes a digitalization framework, designed and developed by following a design science research (DSR) methodology over a period of 18 months. The framework can help practitioners select an appropriate level of sophistication in a DT by weighing the pros and cons for each level, determining evaluation criteria for the digital twin system, and assessing the implications of the selected DT on the organizational processes and strategies and value creation. Three real-life case studies illustrated the application and usefulness of the framework. DOI: [10.1061/\(ASCE\)ME.1943-5479.0001034](https://doi.org/10.1061/(ASCE)ME.1943-5479.0001034). © 2022 American Society of Civil Engineers.

## Introduction

Digitalization offers numerous possibilities to improve performance and productivity within the architecture, engineering, and construction (AEC) industry (Hampson and Tatum 1993). One such technology that has received a great deal of attention recently is the digital twin (DT) (Boje et al. 2020; Grieves and Vickers 2017). It promises to give a multidimensional view of how an asset will perform by simulating, predicting, and informing decisions based on real-world conditions (Autodesk 2021). A recent Gartner survey revealed that by 2022, over two-thirds of the companies that have implemented sensor technology anticipate to have deployed at least one DT in production (Gartner 2019).

However, there is no so-called universal DT that everyone can deploy. DTs have a wide variety of sophisticated capabilities, ranging from simple digital representation (Canedo 2016; Schroeder et al. 2016) to increasingly complex models with predictive and prescriptive capabilities (Gabor et al. 2016; Glaessgen and Stargel 2012). Naturally, the technological capabilities, resources needed to build a DT, and the value that a DT adds to a business will differ in every case, as well. Therefore, for a successful deployment of a DT, managers and practitioners need to select an appropriate level of sophistication in a DT, articulate the technological requirements to build it, and clearly communicate the strategic vision for its implementation to the top management.

However, given these varied possibilities that DTs can offer, practitioners themselves are confused, and face increasingly difficult decisions regarding what type of technological capabilities to select in a DT when deploying it in the AEC industry (Shao and Helu 2020; Feng et al. 2020; Agrawal et al. 2022). A lack of understanding by practitioners and a company's management regarding the type of capabilities needed in a DT can result in unrealistic expectations of the technology (Love et al. 2020), strategic misalignments (Hampson and Tatum 1993), misallocation of resources, inability to realize benefits from the technology (Love and Matthews 2019), and, ultimately, a rejection of DT as hype (Wright and Davidson 2020).

This paper answers the following research question: Given the wide range of possibilities that DT can offer; how should practitioners select an appropriate level of sophistication in a DT to deploy in practice? Specifically, the paper facilitates this process of selection for practitioners by proposing the digitalization framework. This framework highlights two perspectives that should be kept in mind when selecting the sophistication of a DT: (1) the business value that the company expects from DT deployment, and (2) the technological capabilities the company possesses to develop a DT. The framework further helps to align these two perspectives, thus helping practitioners evaluate and understand the different forces in play when deploying a DT in practice.

In addition to facilitating the selection of an appropriate level of sophistication in a DT, the digitalization framework helps managers and practitioners understand and highlight various strategic misalignments in the deployment of DTs, inculcate a strategic mindset within the organization, and set up a long-term strategic vision or roadmap for digitalization in the company. Educators and researchers arguably will find value in the highlighted dichotomy between the business value that practitioners expect from a DT and the technological capabilities they possess to build it. Awareness of this dichotomy that practitioners regularly face in practice will enable researchers to develop methods and practices that are more likely to succeed in the actual field deployment of a DT. We thus hope that our digitalization framework, to some extent, can accelerate and steer the adoption of digital technologies in the right direction, which still has been lagging in the AEC industry.

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The paper starts by reviewing the literature in the section "Literature Review." Section "Research Methodology" provides the research and validation method used to develop the framework. This is followed by introducing the digitalization framework in the section "Digitalization Framework." In the section "Application of Framework in Case Studies," three real-life case studies showcase the relevance of the digitalization framework. The paper concludes by discussing the findings and their implications for the AEC industry in the section "Conclusion."

## Literature Review

This section reviews the research context, DT, in the subsection "What is a DT?" and levels of DT in the subsection "Existing Works on Levels of DT". It then focuses on the studies most relevant to this work's focus, methods to select the appropriate level of DT, in the subsection "Relevant Works on Selecting an Appropriate Level of DT." Finally, the observed gaps in the literature are summarized in the subsection "Gaps in Knowledge."

### What is a DT?

The concept of a physical twin, a precursor to DT, is rather old and dates to NASA's Apollo program (Schleich et al. 2017). Identical space vehicles were built, and one vehicle, the twin, remained on Earth. The twin was used to mirror the precise in-flight conditions, run simulations, and thus assist the astronauts with the best possible solution. Therefore, the idea of a twin broadly covers all the prototypes that help to mirror the actual operating conditions.

Naturally, it is costly and almost impractical to construct a physical twin of every asset or entity. Therefore, the idea of physical twinning was extended further to construct a twin digitally. The proposition of digitally twinning an asset or entity that helps to mirror the actual operating conditions but at the same time is less costly and practical is precisely the motivation for the DT concept.

Grieves first presented the idea of DT in 2003 as a digital information construct of the physical system, which optimally includes all the relevant information required to complete the task at hand and is linked with the physical system in question (Grieves and Vickers 2017). The main DT components (Fig. 1) are the (1) physical component, (2) virtual model, and (3) data that connect the components. The data flow from the physical component to the virtual model is raw, and requires processing to convert to helpful information. On the other hand, the data flow from the virtual to the physical world is processed information that can be used to manage the day-to-day usage of the physical entity.

The first formal definition of DT was coined by NASA in 2012 (Glaessgen and Stargel 2012): "an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin." Although the concept originated from the aerospace industry, owing to its usefulness it has spread to

many other industries, such as manufacturing and construction. The following paragraphs summarize various DT applications, implementation themes, and barriers to adoption in these industries.

In the manufacturing industry, the primary purpose of DTs has been to represent a system's complex behavior, considering the possible consequences of external factors, human interactions, and design constraints (Rosen et al. 2015; Gabor et al. 2016). Kritzinger et al. (2018) reviewed over 40 articles on DT application in the manufacturing industry and categorized the focus areas of DT implementation in five specific categories in addition to general manufacturing applications: (1) layout planning for automated production planning and evaluation (Uhlemann et al. 2017), (2) optimization of the product lifecycle (Boschert and Rosen 2016), (3) production planning and control to improve and automate decision support (Rosen et al. 2015), (4) manufacturing process redesign (Schleich et al. 2017), and (5) predicting and managing maintenance (Susto et al. 2015). Cimino et al. (2019) reviewed over 50 articles on DT applications in the manufacturing industry and found a similar categorization for DT focus areas in the manufacturing industry.

Based on reviews by Opoku et al. (2021), Al-Sehrawy and Kumar (2021), and Jiang et al. (2021), applications of DT have been demonstrated throughout an asset life cycle in the AEC industry. DTs have been implemented in the design and engineering phase by using a combination of Building Information Modeling (BIM) and wireless sensor networks (WSNs) to provide designers with efficient real-time information during project design (Lin and Cheung 2020). Du et al. (2020) introduced the concept of a cognition DT, which can provide selective and personalized information to designers and engineers, thereby reducing information overload and improving efficiency. Martinelli et al. (2019) used a DT for cost estimation during the preliminary conceptual design phase. In the construction phase, DT has been used for construction progress monitoring and management (Bueno et al. 2018), construction quality and safety monitoring (Akula et al. 2013), and machine and material monitoring (Zhou et al. 2019). In the operations and maintenance (O&M) phase, DT combined with machine learning (ML) has been used for simplified analysis of energy usage in buildings (Austin et al. 2020). Francisco et al. (2020) proposed a DT-enabled urban energy management platform by enabling identification of building retrofit strategies. DT has also been shown to be effective in data querying and supporting decision-making during the O&M phase (Lu et al. 2020). Several other applications of DTs have been demonstrated beyond the asset management space in the AEC industry, such as enhanced risk-informed decision-making (Ham and Kim 2020), and disaster management (Ford and Wolf 2020; Fan et al. 2020).

Although the aforementioned pilot applications of DTs are motivating, several barriers need to be resolved to enable widespread adoption of DTs. Neto et al. (2020) found from expert interviews that lack of structured project pathways to implement DTs, and organization cultures and strategies that are resistant to change, are the major impediments to DT adoption, highlighting a lack of strategic vision in practitioners and organizations. Wache and Dinter (2020) reviewed the DT literature and found that the current literature focuses solely on technology deployment and underrepresents managerial or organizational points of view, which are critical for DT adoption. Perno et al. (2022) reviewed over 40 articles on DT implementation and found that the barriers for its adoption in the industry were difficulty in making suitable decisions and investments regarding the enabling technologies (Ezhilarasu et al. 2019) and difficulty in identifying clear value propositions associated with DT solutions (Wishnow et al. 2019).

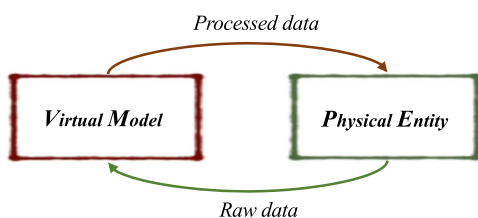


Fig. 1. Digital twin paradigm.

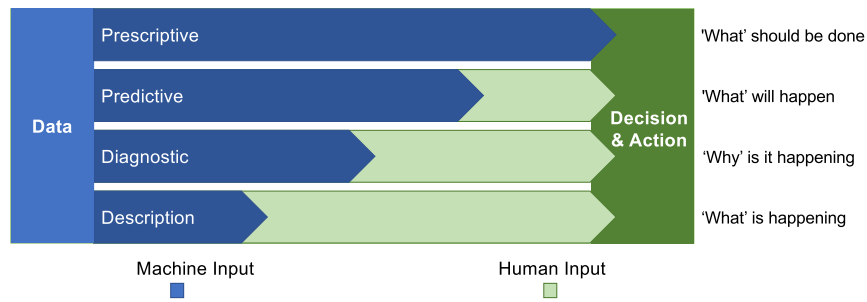


Fig. 2. Levels of analytics capabilities suggested by Gartner.

The digitalization framework can help alleviate the aforementioned problems to some extent. It helps managers make suitable decisions regarding the enabling technologies by selecting an appropriate level of sophistication in a DT. Moreover, it also forces practitioners to articulate clearly the value proposition of a DT by inculcating a strategic mindset and highlighting various strategic misalignments. Finally, the digitalization framework helps create a strategic roadmap, thus addressing the underrepresentation of the managerial perspective. More details of this are provided in the section “Conclusion.”

### Existing Works on Levels of DT

To select an appropriate sophistication in a DT, it first is essential to specify the different levels of sophistication in a DT. The levels of DTs exactly answer to this question and thus describe and compare the different types of DTs. The digitalization framework builds upon the existing models for levels of DTs and helps to select the appropriate level to be deployed in practice. Some of the existing work on levels of DTs are discussed subsequently. Although we showcase the use of the digitalization framework with the levels of DT hierarchy proposed by Gartner, our framework is applicable broadly to any of these hierarchies.

Three different types of DT, depending on the amount of data integration, were described by Kritzinger et al. (2018): digital model, digital shadow, and digital twin. Madni et al. (2019) described the levels of DT maturity: predigital twin, digital twin, adaptive digital twin, and intelligent digital twin. Agrawal et al. (unpublished data, 2021) provided a two-dimensional framework for levels of DTs based on the intelligence capability at each level. Autodesk (2021) described a five-level hierarchy: (1) descriptive twin, which is a visual replica of the asset; (2) informative twin, which captures and aggregates defined data; (3) predictive twin, which uses operational data to gain future insights; (4) comprehensive twin, which generates what-if scenarios; and (5) autonomous twin, which acts on behalf of the users. Gartner (2013) described different levels of digital analytics capabilities that can be present: descriptive, diagnostic, predictive, and prescriptive abilities.

The taxonomy provided by Gartner is one of the most observed hierarchies in the literature. For example, there are many similarities between the hierarchies proposed by Gartner and Autodesk. Davenport and Harris (2017) offered a very similar hierarchy consisting of statistical analysis to answer why questions (similar to the analysis level of Gartner), forecasting and predictive modeling (the prediction level of Gartner), and optimization level (the equivalent of the prescription level). Pyne et al. (2016) also defined the level of data analytics into three levels: description, prediction, and prescription. Nguyen et al. (2018) reviewed over 80 articles on the application of big data analytics in different domains such as

manufacturing, procurement, and logistics management, and reported that the prediction and prescription levels were found in over 40% of the papers, again reinforcing the immense popularity of this taxonomy. Hence, for the scope of this paper, we used Gartner’s taxonomy in the digitalization framework. The taxonomy proposed by Gartner is summarized subsequently.

The rationale of using Gartner’s taxonomy was to examine the extent to which DTs are being used to support decision-making processes (Fig. 2). At the lowest level, a DT only represents the information in a useful form (description). Humans can use this information to make the final decision. At a higher level, a DT goes a step further and reasons why something might be happening (diagnostic). Furthermore, to evaluate different alternatives, at the highest levels, a DT tries to predict the possible future outcome (prediction) and decide upon the action based on the objectives and preferences (prescription).

### Relevant Works on Selecting an Appropriate Level of DT

To the best of our knowledge, no existing work focuses on selecting an appropriate level of DT. However, because the idea of selecting a level of DT is related to technology evaluation in general and the selection of technological capabilities for an organization in particular, the concepts discussed in these related fields are relevant and applicable to our research. Therefore, a summary of the existing literature is provided as a precursor to the digitalization framework.

For years, in the broader strategic management literature, scholars have been juxtaposing the forces that shape technology selection (Schmookler 2013; Myers and Marquis 1969; Rosenberg and Nathan 1982). Primarily, two major models have been proposed to guide the selection of appropriate technological capabilities: (1) need pull, and (2) technology push (Chau and Tam 2000; Nemet 2009; Horbach et al. 2012; Di Stefano et al. 2012). In the AEC literature, Nam and Tatum (1992) observed similar models guiding the technology selection process among construction companies. The following paragraphs summarize these two prominent models for technology selection and detail how they relate to the digitalization framework.

The need pull model assumes that the problem (or the need) to be solved acts as the driving force for selecting the technological capabilities. Popular technology evaluation methods such as comparing the internal rate of return, payback period, and strategic fit (Milis and Mercken 2004; Love et al. 2005; Stockdale et al. 2006) fall into this category. They all, in some form, select the technology based on the expected value, even if the precise definition of value varies across each method.

Although the need pull model might seem very intuitive, it is not suitable when the problem is not detected a priori, or when the

technology cannot solve the predefined problems. Moreover, the developments associated with big data and technology exaggerate this further. For example, much of the data collection today is not intentional (or planned to solve a problem) (Varian 2010). It is haphazard, heterogeneous, and messy. These data sometimes can uncover nontrivial insights into the problems which were not originally intended or planned. To alleviate this issue, the technology push model suggests technology acting as a lead instead of reacting to the business problem. It selects the existing technology capability for deployment and searches for an appropriate problem it can solve. However, this approach lacks critical evaluation of the business value (Love et al. 2020) and the corresponding changes required in the organizational conditions to sustain the value (Love and Matthews 2019), resulting in the inability to realize the purported benefits of the technology.

It is quite apparent that both models have their pros and cons. Therefore, to alleviate the shortcomings, Burgelman and Sayles (1988) and Brem and Voigt (2009) suggested an appropriate alignment between the approaches. This idea of alignment between need pull and technology push to select technological capability forms the central theme of the digitalization framework. This is discussed further in the section "Digitalization Framework."

### Gap in Knowledge

To enable widespread adoption of DT in practice, there is a need to enable practitioners to select an appropriate level of sophistication in a DT. In addition, a framework or method is needed which can allow the practitioners to create a strategic roadmap for the implementation of the DT. The existing studies in the literature do not address these issues sufficiently.

A review of the literature revealed that although there are several methods for general technology evaluation and selection, none of them have been used in the context of DTs. Moreover, the prominent models for selecting general technological capabilities highlight a seeming dichotomy. On the one hand, the need pull model focuses on the problem and does not consider whether the technology can deliver the envisioned value. On the other hand, the technology push model ensures that the technological capability is available at the starting point, but tends to miss the business value analysis.

To address the gap in knowledge, this work focused on building a digitalization framework for the deployment of DTs in the AEC industry. It considers both the need pull and the technology push perspective, and emphasizes the need to align both approaches. The findings were validated through expert feedback following a design science research methodology.

### Research Methodology

The digitalization framework was developed and validated over the course of 18 months using the design science research or constructive research methodology (Holmström et al. 2009). The DSR methodology allows for practical problem solving along with theoretical knowledge creation (Geerts 2011), which typically cannot be achieved by research methods such as surveys and questionnaires (AlSehaimi et al. 2013). It tends to focus on describing, explaining, and predicting the current natural or social world by not only understanding problems but also designing solutions to improve performance (Van Aken 2005). Specifically, the DSR methodology develops constructs (e.g., conceptual models, methods, frameworks, or artifacts) that are relevant in practice and, at the same time, ensure conceptual rigor. These constructs do not describe the existing reality like the approaches in explanatory sciences (e.g., sociology and natural sciences), but instead help create a new desired reality (Järvinen 2007).

Because the digitalization framework was built to provide a rigorous conceptualization for selecting a level of DT, one that is relevant in practice, the DSR methodology was a good fit. The DSR methodology has been used to develop several practical and technological artifacts in the construction industry. Oyegoke and Kiiras (2009) used the constructive approach to develop an innovative procurement method for improving owner contracting strategies. Tezel et al. (2021) developed a blockchain model for supply chain management in construction. Chu et al. (2018) used the DSR methodology to develop a framework for integrating BIM and augmented reality in construction management.

Following the DSR methodology suggested by Peffers et al. (2007), a five-stage process for the development of the digitalization framework was followed (Fig. 3): (1) problem identification, (2) defining research objectives, (3) framework design and development, (4) framework demonstration and evaluation, and (5) framework usefulness testing.

In Stage 1, we identified the problem through self-reflection and an initial literature review as described by Hevner and Chatterjee (2010). A practitioner's problem selecting appropriate capabilities in a DT was observed during an ethnographic action research study (Agrawal et al. 2022). The existence of the problem was validated further through a literature review, as summarized in the section "Literature Review."

Stage 2 involved defining specific research objectives for the study. We met with three industry experts to formulate the vision for the project: develop a detailed and validated digital strategy framework to gain actionable insights, emphasizing the potential benefits of DTs in the context of an organization or a specific

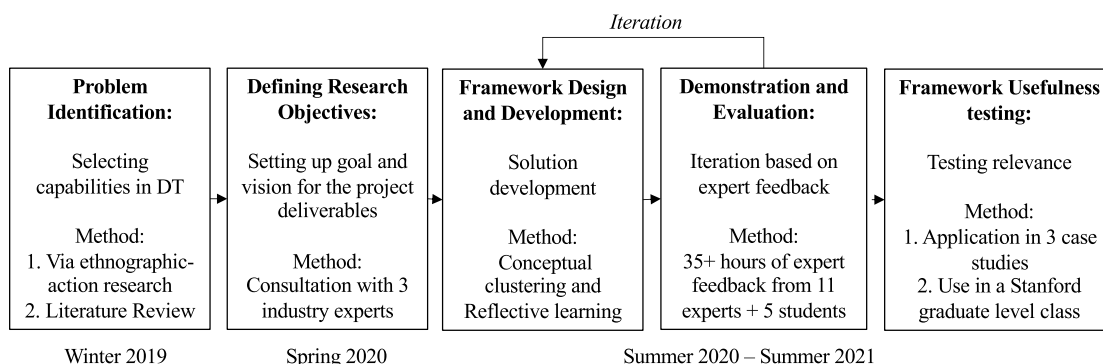


Fig. 3. Research methodology.

**Table 1.** Profile of experts

Type of experts	Expert code	Background/role	Experience (years)	Number of meetings	Total hours of interaction
Industry experts	A	Senior manager in a construction firm	20–25	3	3
	B	Project manager on a \$1 + billion project	25–30	1	2
	C	Senior manager in a construction firm	15–20	2	1
	D	Head of innovation in AEC firm	20–25	2	1
	E	Management executive in AEC firm	30–35	1	1
	F	Project manager in a construction firm	10–15	3	2
	G	Innovation lead with a general contractor	10–15	1	1
	H	Researcher in use of AI in AEC industry	30–35	5	5
	I	Expert and researcher in business strategy	35–40	2	2
	J	Researcher in innovation management	10–15	3	3
	K	Researcher in technology deployment	20–25	2	2
Graduate students	S1	Researcher in deployment of ML in AEC industry	0–5	3	3
	S2	Researcher in virtual design and construction	5–10	5	5
	S3	ML researcher in AEC industry	0–5	1	1
	S4	Researcher in industrial facilities management	0–5	1	2
	S5	Researcher in building operations management	0–5	1	1

Note: Total 23 h interaction with 11 experts and 12 h interaction with 5 graduate students over 18 months.

project. The research objectives and the initial project proposal were documented digitally (Fischer and Agrawal 2020).

Stage 3 (framework design and development) and Stage 4 (demonstration and evaluation) happened simultaneously in an iterative manner. The framework design and development followed a process similar to those used by Succar and Poirier (2020) and Agrawal et al. (unpublished data, 2021). The initial development of the framework was conducted to understand how people selected technological capabilities in a DT. For this, we conducted an extensive literature review (described in the section “Literature Review”). Following interactive field research and executive experience methodology, as described by Burgelman and Siegel (2007, 2008), we supported the initial framework development with additional data obtained through our broad academic, executive, and consulting experiences gained over many years.

The initial framework development aimed to answer questions such as

- What themes or factors affect DT selection?
- Do these factors have to support or oppose each other?
- Who is responsible for aligning these factors?

The themes and concepts for the framework were identified using retroduction, conceptual clustering, and reflective learning (Shapiro 1992; van der Heijden and Eden 1998; Walker et al. 2008) based on the answers to the questions.

After a preliminary version of the framework was prepared, it was demonstrated to experts (Table 1) for feedback, and multiple design and development iterations were carried out. The experts were selected based on three factors: (1) practical experience and conceptual knowledge in the topics covered by the study (e.g., DT, technology adoption, technology strategy, and innovation management), (2) diversity of professional roles held by the experts to ensure complementary skills and thinking, and (3) willingness of the experts to be involved in multiple feedback sessions over next several months.

The demonstrations and feedback sessions were in the form of regular check-ins with the experts. More than 30 meetings with 11 experts and 5 graduate students, totaling about 35 h, were conducted during 18 months. The demonstration sessions with the experts were semistructured and followed a protocol similar to that used by Agrawal et al. (unpublished data, 2021). The session started with presentation of the latest iteration of the framework to the experts and recording their feedback. The experts were asked to

comment specifically on four parts: (1) elements of the framework that made sense, (2) elements of the framework that needed to be improved, (3) perceived helpfulness of the framework in practice, and (4) perceived comfort level in using the framework in practice.

The feedback from each session was incorporated into the next iteration. Multiple meetings with the same expert were conducted to ensure that the feedback was incorporated appropriately. These design iterations were carried out until theoretical saturation was reached, i.e., no new or relevant feedback emerged from the demonstrations (Glaser and Strauss 2017). To provide a trail for the development of the framework, three old but pivotal versions of the framework were documented digitally: digitalization pyramid, spring model, and the three-force three-factor model (Fischer and Agrawal 2019, 2020).

Finally, in Stage 5, to analyze the practical usefulness, two studies were conducted

1. The framework was applied along with practitioners to three real-life case studies to determine if it could provide actionable insights. Details of these case studies are given in the section “Application of the Framework in Case Studies.”
2. To further validate that the framework can be used independently, the digitalization framework was used in a 3-month, graduate-level project-based class at Stanford University. The students (in a total of five groups) applied the framework in their projects involving DT implementation for a commercial company. It was found that the framework is helpful to highlight the alignments and misalignments between the business and technology strategies. The framework also was found to be useful in setting informed management expectations at the beginning and creating a technology implementation plan. The course description, project description, and the class syllabus were presented by Fischer and Agrawal (2021).

## Digitalization Framework

The digitalization framework is an integration of two different perspectives (Fig. 4) of technology deployment existing in the strategic management literature.

The need pull perspective is anchored in the notion that business needs, when a company’s management wants to achieve a particular value or a competitive advantage, are the reason for deploying

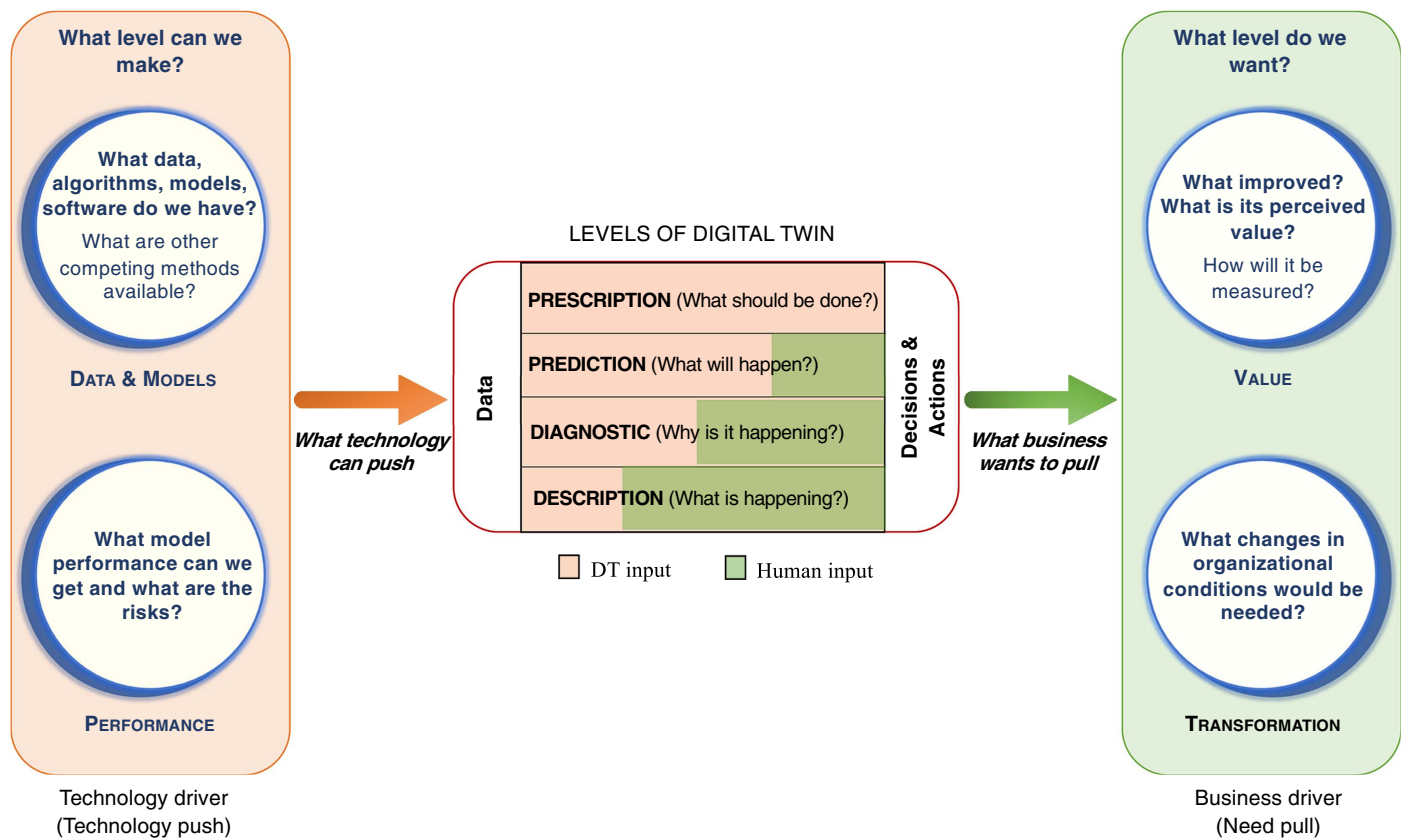


Fig. 4. Digitalization framework.

a DT. Therefore, in these situations, the problem (or the need) that is to be solved through a DT is clear and acts as the driving force for selecting the appropriate level of DT and the technological capabilities needed to support it. For example, consider a case in which a firm is seeking a way to improve highway maintenance because the current process of managing the highway is very inefficient. In this case, the driver for the deployment of DT is the need to improve the current maintenance process of the highway. The firm would try to determine the top causes of this inefficiency and build a DT that can solve them.

The technology push perspective describes technology as a driver for deploying new solutions. In these situations, a technology champion, or any other person in the company who is fascinated by technology developments, decides to change something. This scenario may not be motivated necessarily by a pressing need in the first place, and might require searching for an appropriate use case for deploying the technology. For example, a firm can be fascinated by the recent developments in ML and artificial intelligence (AI), and may search for some use cases to improve the current business.

In essence, the need pull perspective emphasizes the business strategy informing the technology deployment, and the technology push perspective emphasizes the need to change the business strategy according to the evolving technological capabilities. We feel that both perspectives are equally important. A DT deployment motivated by a problem in hand, and lacking the technological capabilities to build it, will lead to unrealistic expectations from the technology and ultimately to failure and frustration. On the other hand, deploying a DT just because of the technology fascination can result in wastage of resources and unrealized benefits from the DT.

Therefore, the digitalization framework emphasizes the need to align both these approaches for successful deployment of DTs in

practice, as highlighted by Burgelman and Sayles (1988) and Brem and Voigt (2009). Although, in practice, the main driver for the deployment of a DT can be either of these perspectives, it is essential to keep the other part in mind. Hence, the framework emphasizes the level which the technology can push and the level which the business wants to pull.

Fig. 4 shows the two perspectives in the context of levels of DTs, with the technology driver on the left and the business driver on the right. The business driver is based on the elements value and transformation, and the technology driver is based on the elements data and models and performance. Each of these elements is explained subsequently. The central element, levels of DT, is generalizable, and any DT hierarchy can be used. This paper used a hierarchy inspired by Gartner, as explained in the section "Literature Review."

1. **Value.** In essence, the purpose of a DT is to improve the current ways of working in some form or the other. Therefore, it becomes important to ask what has (or will be) improved through the use of a DT, and what value does that improvement bring to the business. Value defines the extent of impacts that the organization wants or expects from using a technology (Renkema 2000). It also anchors the firm's business strategy, ensuring that the correct problem is being solved, and thus drives the design of technological solutions. Lack of value evaluation of the technology confounds the organizations to realize the purported benefits of digitalization (Love and Matthews 2019).

Many construction organizations do not evaluate technology for value creation, and those that do use very broad qualitative value definitions such as improved growth and success or improved market share (Love et al. 2004). The defined value should be quantified, measurable, and directly affected by the

technology implemented. Defining the value too narrowly overlooks commonalities and linkages across different aspects of the product, the process, and the organization delivering it. On the other hand, an unquantified, broadly defined value makes the definition poor and vague, leading to no mechanism to remind the team of goals once work has begun (Fischer et al. 2017).

2. **Transformation.** Value cannot be delivered without change (Peppard 2016). Benefits of technology deployment are marginal if only superimposed on the existing organizational conditions (Venkatraman 1994). Love and Matthews (2019) noted that to realize the purported benefits of technology, asking a series of “how” questions is essential. Therefore, to accrue the maximum benefits from DT deployment, it becomes important to ask what changes in organization conditions would be needed. An ethnographic action study by Agrawal et al. (2022) reported that the magnitude of the changes required in the organizational processes to sustain the value generated by DT is commensurate the technological capabilities that a DT possesses. A higher level of DT can lead to radical changes in an organization compared with a lower level of DT. An example of this is provided in the section “Application of the Framework in Case Studies.”

3. **Data and Models.** Real-world problems are complex, with many unknowns. The end product that is sought is a piece of code (and possibly some hardware) that can solve the problem. However, there is a huge chasm between the problem and the solution. Algorithms and models translate real-world problems into mathematical objects that the computer can understand and work upon. Thus, the models and algorithms, which in turn depend on the data and programming abilities in hand, to a large extent determine the types and extent of cognitive ability in a DT.

To ensure appropriate technological capability for deploying a DT, it is important to ask what data, algorithms, models, software the organization has. Generally, modeling is lossy and cannot capture all the richness of the real world. British statistician George Box famously said (George E. P. Box. 2022), indicating that a model will never reflect the exact real-world behavior. This makes it important to ensure that the model explicitly captures the part of the real world that is important for answering the user’s question, again highlighting the need for alignment between the two perspectives.

4. **Performance.** A DT is evaluated against a performance measure. In other words, it is the point at which one can say that the model (and algorithm) is good enough for deployment. It includes all the desirable qualities such as having high accuracy, performing the task in minimum possible time, and requiring minimum human effort. Some of these goals conflict, and a trade-off is necessary. Thus, it is essential to estimate the required performance levels for each goal and set the relative importance between them based on the risks involved. From practice, we have observed that practitioners tend to

a. Confuse value and performance measures—we often have seen practitioners defining the performance requirements for a DT as “reducing the cost of the project,” “speeding up the decision latency,” and “increasing safety on the site.” These sample excerpts by the practitioners are the value that can be derived from a DT, not the performance measure against which DT would be evaluated. Sample performance measures in these cases would be 60% faster schedule creation (leads to the value reducing the cost of the project), and automated decisions within 30 min of a query with at least 90% accuracy (leads to the value decreasing decision latency).

b. Set up qualitative performance requirements—we also have observed practitioners setting up requirements such as “high accuracy,” “good level of accuracy,” and “within a reasonable time.” Such qualitative requirements are impossible for the model to interpret, and thus become a hindrance in building a model that can be deployed in practice. We suggest that the defined performance requirements should be interpretable by any randomly selected person without using their judgment. For example, a performance requirement defined as “good accuracy” is subject to the judgment of the person of what is “good,” but a requirement defined as “at least 90% accurate” is objective and does not require any judgment.

After introducing the digitalization framework, it is important to showcase its applications in real-world case studies. Section “Application of Framework in Case Studies” presents three real-life case studies using the digitalization framework. Section “Conclusion” follows by expanding on the findings and additional use cases of the framework.

## Application of Framework in Case Studies

Perhaps the most appropriate test of the usefulness of a conceptual framework is whether practitioners in companies find value applying it in practice. Therefore, to bring the framework to life, we demonstrate the framework’s application in three real-life case studies. Although its application in three case studies cannot prove the generality of the framework’s usefulness, we tried to demonstrate the application across different project phases with different types of AEC firms situated in various parts of the world.

The first case study was of construction engineering company and was retrospective, to identify if the framework partly could have helped resolve the company’s issues during the project. The second case study was of a full-service engineering firm and was prospective, in which the framework was applied in the planning/pilot phase to help the project team better understand the plausible issues that could arise while deploying a DT. The third case study was of a general contractor and was applied in real-time during the project, and it helped solve some of the team’s issues.

### Case Study 1: DT Deployment on Wind Turbine Project

#### Situation Description

The case study focused on a construction firm involved in the project of installing and maintaining wind turbines. One of the cranes installing the wind turbines on the project recently tipped over due to soil failure. Crane failures are extremely dangerous and costly for the project. The project team thus realized the importance of calculating the soil bearing capacity before walking the crane. They estimated that the manual method of data collection, data processing, and calculation takes about 8 weeks to produce results, which was unacceptable. Thus, the team envisioned creating a DT of the installation site, which can have the real-time data of soil and topography and predict the soil capacity instantaneously via machine learning.

#### Key Events

1. The project manager (R) selected prediction as the level of DT and envisioned using a DT to collect real-time soil data and predict the soil capacity using ML.
2. R defined the value from the DT as improving the soil capacity calculation time from 8 weeks to real time via prediction from the ML model, which would help the company to have zero crane tip-overs.

3. R checked with the senior management regarding the transformation and decided to (1) hire a data science team to build the model; and (2) change some of the current decision-making policies in the company regarding the crane walk, which were based on manual observations rather than data-backed calculations.
4. The data team built a model achieving an accuracy of 90%, which R stated was unacceptable. The data team told R that obtaining a higher accuracy would require more data and sophisticated models that the company did not have at that time.
5. R realized that they did not have the technological capability to support the prediction level. Thus, R decided to move to a lower level of DT, description, in which the DT can help collect and preprocess the data. The calculations still will be done manually. Although the team can not obtain instantaneous results, this helped reduce the time from 8 weeks to 3 days.

### Observations and Insights

Although the project team eventually reached an appropriate level of DT, the whole iterative process took them about 3 months. The main issue was uninformed expectations from the technology; the team lacked clarity about what the technology could and could not do. ML was selected partly due to technology fascination rather than following a rational selection approach. One of the members of the data science team stated "If R had told us at the start of the project that they were looking for accuracy of over 99.9%, I would have said upfront that this would be very difficult to get with the amount of data we have."

Retrospective analysis with R revealed that the project team did not formulate the performance element of the framework or define what a good model means for their scenario. R further added that the team was utterly confused about what a good model might mean and that different people had different opinions about it. Due to a lack of formulation of the performance element, the project team could not anticipate what the DT could deliver, leading to unrealistic expectations of the DT. On the other hand, the data science team did not have an objective way to evaluate their ML models. They used their experience to anticipate that 90% should be a good enough accuracy, failing to comprehend the gravity of the situation: a 90% accuracy means that there is a chance that 10 of 100 cranes can fail.

From our experience, we have observed that this is a common scenario, in which the project team is indecisive and unable to articulate the performance they want from a DT. This often leads to misalignments between what technology can deliver and what the business wants, as demonstrated in this case study. Although all other elements of the framework were relatively well defined in this case study, the lack of one element resulted in the misalignment, highlighting the importance and the need to pay attention to all the aspects of the framework.

Because this was a retrospective case study, we cannot test whether the situation would have been different if the digitalization framework had been used. However, R did acknowledge that possibly using the digitalization framework at the start of the project could have helped the project team align their expectations of the DT. This would have enabled a better selection of the appropriate level of DT and possibly reduced the 3-month turnaround time.

## Case Study 2: DT Deployment on Highway Maintenance Project

### Situation Description

The case study focused on a \$1.35 billion publicly owned toll road (SH-130 in Austin, Texas) stretching over 41 mi. The toll road was opened in 2012 and is operated and maintained under the terms of a

50-year facility concession agreement with the Texas Department of Transportation (TxDOT). The performance requirements indicating the minimum expected performance levels and the defect resolution times were set in the SH-130 concession agreement by the Department of Transportation (DoT). Some requirements necessitated a very stringent response time: 6–24 h. Failing to respond adequately could result in heavy fines and risks to the life safety of the users. The manager (B) on this project wondered if a DT could help in some ways.

### Key Events

1. B envisioned creating a DT of the roadway. Because the framework was applied in the planning phase, B did not have an a priori level of DT in mind and was open to brainstorming and suggestions.
2. B defined the envisioned value from DT as reducing operational costs through early detection and preventative maintenance. Detecting the defects early would give the firm more time to resolve them, thus helping them achieve a lower operating cost and move toward a preventive maintenance system.
3. B identified that early detection of defects could be achieved by the description level of DT. A computer vision algorithm equipped in a DT can help it detect defects from real-time data collected via drone imagery of the roadway.
4. B then defined the technological capabilities needed to build this DT and found that the DT seemed feasible with the capabilities that the firm currently possessed.
5. For the preventive maintenance system, B wondered if a DT also could help to predict the potential occurrence of cracks and defects. They checked the technological capabilities needed and found them to be appropriate for their requirements.
6. When B began to formulate the transformation needed at the prediction level of the DT, some nontrivial insights emerged.

### Observations and Insights

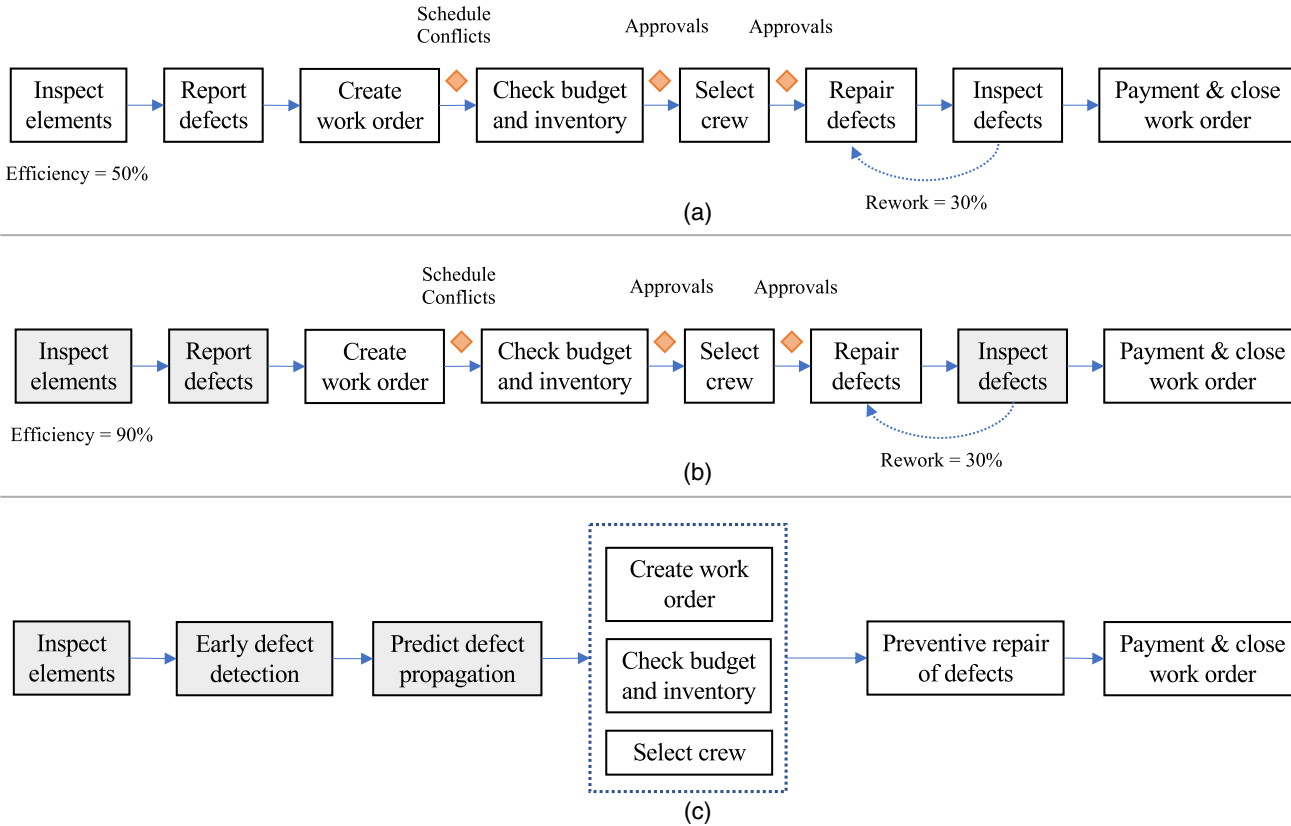
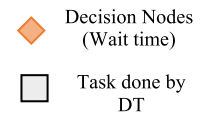
While applying the digitalization framework during the planning phase of DT deployment, B observed that the DT had a significant impact on the corresponding organizational conditions.

Fig. 5(a) shows the process followed by the firm for highway maintenance. The process starts by inspecting the elements and reporting any observed defects during the patrolling and inspections. This is followed by work-order creation, checking of required budget and inventory, and designating the appropriate crew for pothole repair and inspection. Humans are not very efficient at detecting pavement defects.

The description level of DT only informs about the current situation of the world. This function previously was performed by the highway patrol team consisting of engineers and the maintenance staff. With the deployment of a DT, the process of detecting the defects, creating work orders, and inspecting the defects can be automated. A DT would be able to detect the defects and understand the changes that happen over time. Therefore, B would need to make small changes in the organization and shift the personnel previously dedicated to these tasks to more-productive tasks [Fig. 5(b)].

On the other hand, when the company moves to the prediction level of DT, many process changes are required [Fig. 5(c)]. Due to the strict guidelines, the SH-130 concession company needs to keep a large amount of inventory and contact individual subcontractors in a short period to carry out the repair work, leading to unnecessary costs for the company. With a DT making predictions, the team can plan for the material, crew, and equipment in advance. This modifies several of the steps in the workflow and allows them to be completed in parallel instead of sequentially [Fig. 5(c)]. For example, on January 1 of every year, the company can query the defects that are expected to appear and create advance work





**Fig. 5.** (a) Original workflow; (b) changes in workflow with DT at description level; and (c) new workflow with DT at prediction level.

orders, thereby removing the latency and decision-making time. The company also can pivot to a just-in-time delivery method for materials and equipment delivery. However, moving to this kind of system would require significant remodeling of the current ways of working, such as changing the existing contracts, legal tenders, and business partnerships, again emphasizing the significance of transformation to sustain the value provided by a DT.

In a semistructured interview, B acknowledged that the digitalization framework acted as a structured planning tool, forcing the project team to think through the process of DT deployment and articulate the transformations needed in the organization. B also added that the framework enabled him to communicate his strategic vision for DT deployment clearly to the top management, along with the corresponding changes needed in the organization. A follow-up interview with an executive from the top management of the company revealed that the framework helped them achieve clarity on DT deployment and made them much more confident about the project roadmap ahead. Ultimately, a successful deployment of a DT would depend on resolution of these and many other factors.

### Case Study 3: DT Deployment on Construction Project

#### Situation Description

The first two case studies were driven by the need pull mechanism; each project team sought to solve a specific issue using a DT.

On the other hand, this case was driven by the technology push mechanism; the company's management was fascinated by DTs and sought ways that a DT can add value to the business.

An innovation manager (G) working with a mid-sized general contractor in Norway developed a DT prototype for weekly or daily construction site management combining BIM and the Last Planner System. The system worked very well on a few demonstration projects, allowing foremen and the superintendent to understand the work accomplished throughout the day. Therefore, G expected rapid deployment of the prototype across many projects. This did not happen. Working through the framework helped G understand the issue behind this, at least in part.

#### Observations and Insights

Working through the framework from the technology perspective, it was realized that DT developed by G improved the description of what is happening on site. Some site staff found this improvement helpful. Working through the diagram from the value side with G, it was realized that most site staff really wanted a prescription, i.e., they wanted to know what should be done tomorrow and subsequently. Hence, the insights expected by the business or value perspective were misaligned with the insights that the technology could provide. This was the major reason for the slow adoption of the technology.

In this case study, the digitalization framework was used as a diagnostic tool to detect G's problem in real-time while deploying the DT. The framework helped G understand the misalignment

between what the business wanted and what the technology was delivering. When G understood the root cause of the problem, he decided to communicate clearly the benefits that the DT can provide to the management and thus align the expectations. G also realized the need for the prescription level, as suggested by the staff members, and decided to move to it in the future using ML.

## Conclusion

For a successful deployment of a DT, managers and practitioners ideally should be able to select an appropriate level of sophistication in a DT, articulate the technological requirements to build it, and clearly communicate the strategic vision for its implementation to the top management. However, given the varied range of capabilities that DTs offer, practitioners themselves are confused and face increasingly difficult decisions regarding what type of technological capabilities to select in a DT when deploying it in the AEC industry. This confusion results in unrealistic expectations of the technology, strategic misalignments, and misallocation of resources, ultimately leading to slower adoption of digital technologies in the AEC industry.

Therefore, to alleviate this confusion, the paper presents a digitalization framework that helps practitioners strategically select an appropriate level of sophistication in a DT. The framework brings together ideas from the strategic management literature emphasizing the importance of technology-driven problem-solving (technology push) with ideas that emphasize the importance of a value-driven approach for problem-solving (need pull), and argues that the alignment of both approaches is necessary for a successful deployment of DT. The framework was developed and validated following the DSR research methodology over 18 months. The design iterations and the validation were carried out using the feedback from 11 experts and 5 graduate students over multiple meetings totaling over 35 h. The framework was tested further for usefulness by (1) applying it in three longitudinal case studies; and (2) using it in five student projects in a graduate-level class at Stanford University. The current version of the digitalization framework has been validated and tested only through case studies and expert feedback in the AEC domain. Therefore, the generality and applicability of this framework cannot be claimed outside the AEC industry. Future research can explore the universality of this framework by conducting case studies and expert reviews from other industries as well.

The digitalization framework is intended to be useful for both academics and practitioners. For academics, the framework should help researchers better evaluate their proposed DT applications and models in terms of the business value it provides, the technological capabilities needed to build it, and the organizational changes required to sustain the value generated from the DT. Awareness of these factors would enable researchers to develop models and methods that are more likely to succeed in practice. The framework also should act as a gentle reminder to educators that there probably is less value in defining and envisioning a so-called most ideal or technologically advanced DT. The DT needs to be evaluated for each use case, and a one-size-fits-all approach does not work.

Practitioners should use the digitalization framework as a planning and diagnostic tool to evaluate objectively and understand the different forces in play when deploying a DT in practice, and not to prescribe or declare a level of DT for a particular situation. Specifically, we envision the following three use cases for the framework in practice:

1. **Selecting an appropriate level of DT.** The digitalization framework enables the practitioners to examine different levels of

DT systematically and choose the one that provides the most value in the light of existing technological capabilities. It helps them articulate what DT would provide (business value) and understand what would be required to achieve it (technological capabilities). Jahanger et al. (2021) identified the lack of knowledge regarding the challenges and barriers in digital implementations among owners and contracts as one of the main factors for the lag in adopting digital technology. Therefore, using the digitalization framework as a planning tool, especially at the start of a project and at pivotal intermediate points, helps with clear communication of the goals and thus creates a shared understanding among the participants of what to expect and what resources to allocate, as shown in Case study 1.

2. **Better stakeholder management and formulating a digital strategy.** Reaching an ideal envisioned DT is not a one-shot task. There can be instances of misalignments between what the business expects and what the technology can deliver. Such misalignments often can lead to delayed DT deployment, if not a whole project's dissolution. Lu et al. (2015) reviewed technology implementations in the AEC industry over 15 years and reported that a common reason for unsuccessful technology investments was lack of necessary support from project clients and professional consultants, emphasizing the need for strategic alignment among different stakeholders for successful technological deployment. In such critical situations, the digitalization framework can act as a diagnostic tool by helping highlight and understand the root cause of these misalignments and therefore start a conversation toward its resolution, as shown in Case study 3.

If a business wants to pull a higher level of DT, and the technology cannot push it. In that case, the management has three choices: (1) change their expectations to accept the existing level of DT, (2) invest in building a higher level of DT that can fulfil their expectations, or (3) scrap the project altogether. On the other hand, if a business wants to pull a lower level of DT than the technology can push, such as using BIM only for documentation and representational purposes even though it can offer much more, the management again has three choices: (1) keep using the DT at a lower level, (2) find use cases which can make full use of the DT, or (3) change the current DT to have only the required capabilities. In these scenarios, the digitalization framework helps the managers formulate a long-term vision of which level of DT to reach and a strategic roadmap for reaching it from the current level of DT.

3. **Inculcating a strategic mindset throughout the organization.** Owing to the different areas of expertise in a company, some people might be closer to the technology without understanding the business value, and vice-versa, leading to misalignment in organizational strategies. Ansari et al. (2015) noted that many challenges emerge because the strategies made by top-level managers do not have good effects on the operational level of the organization. Therefore, to avoid missed opportunities, it is essential to have a healthy and open debate among the company's executives of different ranks about the evolving technological landscape and its implication for the business.

The digitalization framework facilitates such strategic conversations, as shown in Case study 2. The jargon-free nature of the framework makes it easy to communicate and internalize its basic lessons (Burgelman and Siegel 2008). Even executives who lack background in either the business strategy or the technical capabilities can reason and understand the other side. Therefore, the natural language form of the digitalization framework can become a useful tool to inculcate a strategic mentality

throughout the organization and stimulate continuous technological discussions.

Ultimately, there is no single universal answer to the question of the capabilities that should be selected in a DT for deployment. The management of the company must continue to evaluate carefully all the possibilities and select the level of sophistication that provides the maximum value with the technological abilities in hand. Business expecting a higher level of sophistication in a DT and the technology not being able to deliver can result in false hopes and ultimately in rejection of DT as hype. On the other hand, technology delivering a highly sophisticated DT the value of which the business does not appreciate can result in missed opportunities and unrealized benefits from the technology. The digitalization framework facilitates the process of selection by forcing the practitioners to articulate the perceived business value and the technological capabilities needed in the DT. Awareness of these factors across the firm can increase the likelihood of a successful deployment and adoption of a DT.

## Data Availability Statement

Some or all data, models, or code generated or used during the study are proprietary or confidential in nature and may be only provided with restrictions. The student reports used for the model validation are confidential but can be provided after signing a non-disclosure agreement (NDA).

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