

Maturity of Digital Twins from An Artificial Intelligence Perspective

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Abstract

Due to its potential to elevate buildings as a system to a level where they turn into cognitive (self-reliant autonomous decision-making and acting) entities, the adoption of Digital Twins (DT) has been significantly increased. Therefore, maturity models have become essential for evaluating and enhancing the advancement in DT to assess the adoption of technology across various industries. The paper proposes a maturity model approach from an Artificial Intelligence (AI) perspective to gain insights into the adoption and implementation of DT in the AEC-FM industry, which distinguishes it from the existing maturity models. Additionally, making a comparison between the interpretation of the term 'cognition' in computer science and its understanding within the AEC-FM industry, presenting pre-classified levels of cognition in literature. In this regard, a literature review is conducted to figure-out the gaps in previous DT maturity model studies. The proposed perspective could cover the missing AI perspective in designing maturity models and provide insights into leveraging the semantics of the term 'cognitive' in the AEC-FM industry. Future research directions could further explore various dimensions of DT maturity models and cognition levels within the AEC-FM industry, considering practical challenges and potential applications of DT implementations in-depth.

Keywords: *artificial intelligence, digital twins, maturity model, the AEC-FM industry*

Introduction

As Digital Twins (DT) becomes increasingly prevalent across various industries including manufacturing, construction, aerospace, healthcare, and agriculture since it is first introduced by Michael Grieves in 2003 (Grieves, 2014), there is a growing need for tools to evaluate its current state and offer insights for enhancement. While there is no commonly agreed definition of DT, in most of the definitions it consists of three main elements: the virtual side, the physical side and the data/information flow (feedback and feed-forward loops) between the physical and virtual to connect them. Maturity models are essential for evaluating the present uptake and offering a structured framework for its ongoing advancement and integration of DT. There are different approaches exist in literature to derive DT development and by this way the maturity.

Grieves, introduced the concepts *Digital Twin Prototype*, *Digital Twin Instance*, *Digital Twin Aggregate*, and *Digital Twin Environment* by further expanding the understanding of DT aspects (Grieves & Vickers, 2017). Kritzenger et al. focused on level of data integrated between physical and virtual environments and defined three different levels which are *Digital Model*, *Digital Shadow*, and *Digital Twin* (Kritzenger et al., 2018). On the other hand, Kart et al. outlined four level of DT based on their capabilities: *Descriptive Twin*, *Diagnostic Twin*, *Predictive Twin*, and *Prescriptive Twin* (Kart et al., 2013).

Numerous maturity models exist in DT literature. However, they defined the maturity levels and dimensions related to capabilities and features of a DT. The aim of this research is to suggest a distinct perspective on assessing maturity by focusing specifically on the AI perspective. Since the ultimate point researchers and industry practitioners aim to reach is developing an intelligent system, DT, capable of *self-reliant autonomous decision-making* or in other word ‘*can think and/or act like human does*’ the way inevitably navigate researchers to focus on terms ‘AI’ and ‘cognition/consciousness’.

Building upon the above premises, this paper aims to investigate following research questions:

RQ1: Classification of the existing DT maturity models?

RQ2: What are strengths and weaknesses of the existing DT maturity models?

RQ3: What should be assessed for a Cognitive DT?

RQ4: The distinction between the determination of Cognition/Consciousness in computer science and the AEC-FM field?

RQ5: How does the proposed AI-based perspective for DT maturity differ from the previously used maturity perspectives?

In the following sections, the paper discusses various DT maturity models and emphasizes the central concepts that form the basis of the proposed maturity perspective.

Existing Maturity Models in DT Literature

Maturity models developed for DT have been devised to evaluate and enhance the adoption of DT across diverse industries. There are eight existing maturity model developed for DT in literature which are from aerospace (Medina et al, 2022), manufacturing (Madni et al., 2019; Hu et al.,2023; Mo et al., 2023), asset management (Chen et al., 2021), construction (Boje et al.,2020; Evans et al., 2019) and smart city (Shemyakina et al., 2022). Figure 1 illustrates the existing maturity models in DT literature.

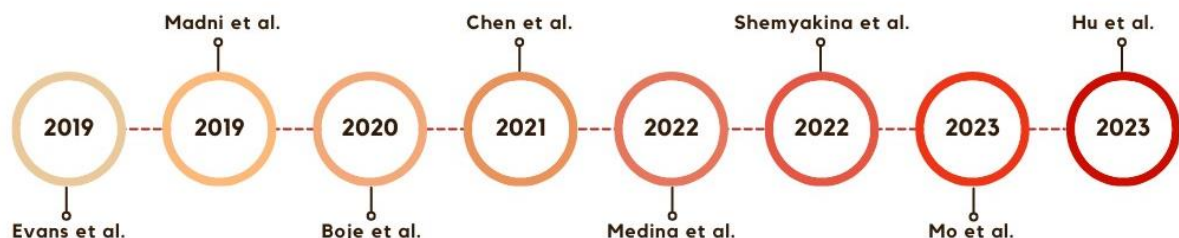


Figure 1. Existing Maturity Models

In the highest level of all existing maturity models, the scenario that the system attains cognitive capabilities is advocated. For example, in the maturity model developed by Evans et al. (2019),

six maturity levels were outlined, with the highest level featuring complete self-governance where the system can conduct autonomous operations and maintenance. At this stage, the system can learn the preferences of humans (generating patterns) and takes minimal action or without human interaction. Mo et al. (2023) identified five levels of autonomy and assessed maturity across various categories, characteristics, and functionalities, for instance a system achieving the highest level of autonomy in 'data integration' can perform self-optimization activities. Similarly, in the model presented by Chen et al. (2021), the system transitions to semi-automatic or fully automatic functioning and is capable of providing decision support independently. Likewise, Madni et al. (2019) asserted that in the highest level of maturity within their developed model, the system demonstrates a high degree of autonomy and possesses supervised, unsupervised, and reinforcement learning capabilities. Although the existing maturity models delve into DT literature and present maturity models based on the definition, features, and functionalities, they fall short in defining the ultimate point a DT can reach according to cognitive capabilities it might have.

Artificial Intelligence (AI) Approaches

Artificial Intelligence (AI) is a field with the potential to transform industries. Since the concept first introduced by John McCarthy (McCarthy et al., 1955), numerous other definitions have emerged, each emphasizing different facets of AI. The ultimate goal of DT, regardless of the industry, is to define a system where the feedback and feed-forward loops between the real world and its virtual representation are completed, thus establishing an endless cycle of development for the data-information-knowledge (DIK) transformation cycle. AI is the primary technology being used in DT, as it offers sophisticated data processing techniques to extract insights from the captured data (Ozturk, 2021). For this reason, the development of a maturity model for DT with cognitive capabilities, the assessment should be centred around AI perspective.

The proposed maturity approach aims not only to create intelligent systems but also to acquire insights into them. In this regard, the categorization of Stuart Russell and Peter Norvig is adopted in this research (Russell et al., 2010). According to their categorization, there are four AI approaches defined:

- (a) Systems that think like human
“The automation of activities that we associate with human thinking, activities such as decision-making, problem solving, learning ...” (Bellman, 1978)
- (b) Systems that think rationally
“The study of the computations that make it possible to perceive, reason, and act” (Winston, 1992)
- (c) Systems that act like human
“The art of creating machines that perform functions that require intelligence when performed by people” (Kurzweil, 1990)
- (d) Systems that act rationally
“Computational Intelligence is the study of the design of intelligent agents.” (Poole et al., 1998)”

Since the time Alan Turing came with the idea of ‘thinking machine’ (Turing, 1950), the focus of AI studies shifted to find ways to create human-like systems. This question triggered another question; ‘can machines ever reach to human cognition level?’ by time and separated

researchers into groups with different perspectives. While some of the researchers think that it will never be possible for a machine (French, 2012; Searle, 2014), some were seeing this as a certain outcome of technological advancements (Bostrom, 2015).

It is essential to understand the distinctions in thinking processes and behaviours to figure out AI approaches. Systems that emulate human thought processes, characterized by intuitive and experiential thinking styles, exemplify the approach of systems that think like human (Hongdizi et al., 2023). An illustration of this approach is seen in Building Occupancy Systems, which can predict future occupancy pattern by analysing the behaviours of human such as working hours and schedules, is a good example for this approach. On the other hand, systems that think rationally rely on logic and deliberate thinking (Pacini & Epstein, 1999). Building Information Modeling (BIM) Systems can be an example to this approach since the aim of these systems are optimization of building lifecycle by analysing several factors such as material cost and energy efficiency. Systems act like human tries to emulate human behaviours and responses. Smart Home Systems can learn and adapt the preferences of humans by time such as turning off lights when there is nobody in room. Lastly, systems that act rationally make decisions and turn them into action based on logic or predefined rules/principles. Intelligent Transportation Systems (ITS) uses rational decision-making strategies to control flow of the traffic or providing real-time data to travellers.

Cognition/Consciousness

Cognition is defined as, the mental processes involved in acquiring, storing, retrieving, and using information from the environment (Mitchell et al., 2002). In computer science literature, cognition has been classified into various levels. This paper adopts David Armstrong's categorization as its framework to reveal what are the required cognition capabilities to create a DT which demonstrates human cognition. Armstrong examined cognition across three distinct levels which are *Minimal Consciousness*, *Perceptual Consciousness*, and *Introspective Consciousness*.

According to this classification, the cognition level of a person sleeping is an example to Minimal Consciousness level. During sleep, humans are unable to perceive even though their sensory organs may be functioning. Regarding Perceptual Consciousness level, objects whose existence has been established in preceding levels are contextualized based on their relationships with other objects. At the Introspective Consciousness Level, the organism not only understands the external world (context) but also comprehends its internal world.

In last years, there is a new effort of combining DT with some semantic technologies process data in a way that human does. DT, as a platform, technology, and service, have potential to facilitate the development of cognitive systems. The term 'Cognitive Digital Twins' firstly introduced during an industry symposium. According to Zheng et al., in the coming years, Cognitive Digital Twin will emerge as the outcome of augmenting traditional Digital Twins with cognitive capabilities and incorporating diverse semantic technologies, such as Knowledge Graphs (KGs) and Natural Language Processing (NLP) (Zheng et al., 2022) (Table 1).

Table 1. Definitions of the term ‘Cognitive Digital Twins’ in the AEC-FM industry

Reference	<i>Cognitive Digital Twins Definition</i>
Saracevic, (2017)	<i>‘a virtual representation of a physical object or system across its lifecycle using real time data from IoT sensors and other sources to enable learning, reasoning and automatically adjusting for improved decision-making’</i>
Fernández et al., (2019)	<i>‘a digital expert or copilot, which can learn and evolve, and that integrates different sources of information for the considered purpose’</i>
Lu et al., (2020)	<i>‘DT with augmented semantic capabilities for identifying the dynamics of virtual model evolution, promoting the understanding of interrelationships between virtual models, and enhancing decision-making’</i>
Abburu et al., (2020b)	<i>‘an extension of Hybrid Twin (HT) that incorporates cognitive features enabling the system to sense complex and unpredictable behaviour, reason about dynamic strategies for process optimization, and continuously evolve its digital structure and behaviour’</i>
Johansen et al., 2023	<i>‘an extended version of traditional DT by integrating machine learning techniques to create hybrid, self-learning, and proactive systems, as well as leveraging the interaction between models and humans to support decision-making processes’</i>

In the AEC-FM industry, cognition is associated with the terms such as ‘autonomous decision-making’, ‘perception’, ‘prescription’, ‘learning’, and ‘integration of different information sources’, ‘advanced technological capabilities’. However, according to meaning of the concept in computer science, cognition is perceived as more intricate than this. Moreover, the level of introspective consciousness remains a topic of debate even among researchers in computer science, and its understanding and application in the AEC-FM industry have yet to be clearly defined.

In contrast to the perspective found in previously developed maturity models, this approach aims to develop a Knowledge Management (KM) perspective focused on the collection, processing, generation of information, storage, distribution, and reuse of data. While the existing maturity models is beneficial in illuminating the current state of DT research and extent of technological capabilities employed, they lack an understanding of the term 'cognition' and human cognitive capabilities. In addition to the concerns addressed in literature such as ‘autonomous decision-making’, ‘prediction’, ‘prescription’, and ‘model update frequency’, the questions related to whether the system is aware of its context or if it can make inferences about its own functioning (introspection) should also be considered. In addition to diverging from the perspectives found in existing literature, the AI-based maturity perspective proposes a comprehensive, structural, and more development-oriented solution for the DT maturity subject.

Discussion

The primary aim behind the development of DT maturity models is to facilitate the adoption and implementation of DT and creating more intelligent, cognitive systems with minimal or no human interaction. AI is the key enabler technology for this purpose. However, the understanding of AI and associated concepts such as cognition varies between the realms of computer science and AEC-FM industry. This paper reviewed existing maturity models for DT

and assessed those put forth by prior researchers. Through this review, gaps and misconceptions in literature are identified.

This study introduces a new approach for developing DT with advanced cognitive capabilities (self-reliant autonomous systems). Although the perspective proposed is better understood within the computer science environment, and its adoption and implementation outside of this domain are still in the early stages, the proposed approach contributes to the current literature and holds potential for enhancing future maturity assessment studies.

Conclusion

The paper proposes a novel approach according to evaluation of maturity of DT after analysing the existing DT maturity models in literature. The proposed method combines elements from different terms and compares the comprehension of AI in both computer science and the AEC-FM industry. While there are challenges in implementing the proposed approach in real-world situations, it holds promise for elevating the built environment from being merely "smart" to more "intelligent". This approach could facilitate the creation of symbiotic systems that integrate the built environment with human interactions, enhancing connectivity and synergy between the two. Future studies might involve developing a maturity model customized for the AEC-FM industry, considering the proposed approach, and/or expanding upon the suggested perspective by incorporating different levels of cognitive classification found in existing literature. The main result of this study is to introduce a novel maturity approach for future studies on digital transformation maturity, aiming to address misconceptions and gaps in the current the AEC-FM industry-based research commenting on cognition and intelligence.

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