Determinants of the propensity to use of digital technologies in the Brazilian construction Industry

Determinantes da propensão ao uso de tecnologias digitais na indústria da construção civil brasileira

Larissa de Moraes Rocha
Luis Felipe Cândido
José de Paula Barros Neto

Abstract

This study analyzes the factors that influence the use of Digital Technologies (DTs) in the Brazilian construction industry. Based on the literature, a theoretical model with 10 factors (30 variables) was initially proposed. Through Exploratory Factor Analysis and Confirmatory Factor Analysis using Structural Equation Modelling, this structure was refined to 7 factors (25 variables). Data were collected via a survey of professionals in the Brazilian construction industry, yielding a final sample of 144 valid responses. Key findings reveal that BIM (Building Information Modeling), Cloud Computing, Unmanned Aerial Vehicles, and Virtual Reality are the most widely used technologies. These technologies are primarily applied in Design/Feasibility, Construction Management, and Execution phases. Moreover, the study confirms the importance of Perceived Usefulness, Organizational Aspects, Necessary Resources, and Current Capacity to use DTs. On the other hand, Ease of Use, Business Environment, and Lean Construction were not found to be significant factors influencing DT adoption. The results provide a comprehensive overview of the current use of DTs in Brazil. Additionally, they offer insights that can aid policymakers and industry managers in promoting digital transformation.

Keywords: Digital transformation. Construction management. Digital technologies. Construction Industry.

Resumo

*Este estudo analisou os fatores que influenciam a adoção de tecnologias digitais (DT) na indústria de construção brasileira. Com base na literatura, foi proposto um modelo teórico com 10 fatores (30 variáveis), que foi refinado por meio de Análise Fatorial Exploratória e Análise Fatorial Confirmatória com Modelagem de Equações Estruturais, resultando em 7 fatores (25 variáveis). Foram utilizados dados coletados por meio de uma survey com profissionais do setor, resultando em uma amostra de 144 respostas. Os resultados revelam que o BIM (*Building Information Modeling*), computação em nuvem, veículos aéreos não tripulados e a realidade virtual são as tecnologias mais usadas. Essas tecnologias são aplicadas principalmente nas fases de projeto/viabilidade, gerenciamento de construção e execução. Ainda, o estudo confirmou a importância da utilidade percebida, aspectos organizacionais, recursos necessários e capacidade atual no uso de DT. Por outro lado, a facilidade de uso, o ambiente de negócios e a construção enxuta não foram considerados significativos. Esses resultados fornecem uma visão abrangente do uso atual de DTs no Brasil. Além disso, podem ajudar os formuladores de políticas e gerentes do setor a promoverem a transformação digital.*

Palavras-chave: *Transformação digital. Gerenciamento da construção. Tecnologias digitais. Indústria da construção.*

[1]**Larissa de Moraes Rocha**
[1]Universidade Federal do Ceará
Fortaleza - CE - Brasil

[2]**Luis Felipe Cândido**
[2]Universidade Federal do Ceará
Crateús - CE - Brasil

[3]**José de paula Barros Neto**
[3]Universidade Federal do Ceará
Fortaleza - CE - Brasil

Recebido em 31/01/25
Aceito em 31/03/25

Introduction

The use of Digital Technologies (DT) has driven the construction industry, improving its competitiveness, economy (Wang *et al.*, 2024), productivity, and construction site safety (Chen *et al.*, 2022; Oke *et al.*, 2024a). DT encompasses the use of communication, computing, connectivity, and information technologies to enhance activities and operations (Verina; Titko, 2019). Through its application, the construction sector has moved towards digital transformation.

However, the diffusion of these technologies remains slow, leading to different adoption rates across the construction industry chain and among different regions (Aliu; Oke, 2023). The construction industry lags behind other industries in the adoption of new technologies (Hwang; Ngo; Teo, 2022). Consequently, many studies have sought to understand the factors preventing and driving DT adoption around the world, including in countries such as China (Wang *et al.*, 2024; Zhang *et al.*, 2023), India (Bajpai; Misra, 2023; Dolla; Jain; Kumar Delhi, 2023), Nigeria (Oke *et al.*, 2024), Malaysia (Almatari; Chan; Masrom, 2024), New Zealand (Chen *et al.*, 2024), Singapore (Hwang; Ngo; Teo, 2022) among others. The studies show that differences in adoption rates depend on many factors such as professional profiles, organizational aspects (Aliu; Oke, 2023; Dolla; Jain; Kumar Delhi, 2023), and the business environment (Chen *et al.*, 2022).

Particularly in Brazil, there is a lack of information on the current use of DT. Studies on this subject remain scarce in the country. For example, Tanaka, Matsuda and MacLennan (2024) conclude that the Brazilian construction industry lags behind other economic sectors in terms of digital maturity. However, their study focused on only two construction companies. In turn, Fernandes and Costa (2024) developed a conceptual model for measuring the maturity of an intelligent construction environment. Again, the sample is limited, and the authors do not calculate the maturity of the companies.

Only two technical reports conducted by BIM Fórum Brasil in partnership with the Federal Council of Engineering and Agronomy (CONFEA) and the Council of Architecture and Urbanism (CAU/BR) provide a broad diagnostic of the use of DT in the Brazilian construction industry (BIM Fórum Brasil, 2022a, 2022b). Despite these efforts, no studies have examined the factors that influence the use of DT, a research gap that this work contributes through the following research questions: Which digital technologies are utilized in Brazilian construction industry? In which project phases are these technologies applied? What factors determine the propensity to use DT within the Brazilian construction sector?

Thus, this study analyzes the factors that influence the use of DT in the Brazilian construction industry. Specifically, it identifies the main technologies applied and the project phases in which these technologies are used; and tests a theoretical model that explains the propensity to use DT within the Brazilian construction industry.

The study expands the understanding of DT use in the Brazilian construction industry, including the factors that influence this use and the propensity to adopt DT. The developed model provides a more in-depth comprehension, which can help policymakers and managers in promoting the digital transformation of the Brazilian construction industry and potentially in other developing countries.

Literature review and research hypotheses

In this section, an overview of previous studies on Digital Technology and its applications in the Brazilian construction industry is provided. Then, the underlying mechanisms governing technology adoption, based on the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM), are discussed. These theories support the proposition of the Theoretical Model and the research hypotheses.

Digital technologies and their uses in the Brazilian construction industry

The construction industry, as other economic sectors, is experiencing paradigm shifts as Digital Technologies (DT) gain momentum (Wang *et al.*, 2024). In this work, DT is understood as the employment of technologies to radically improve the performance of organizations (Westerman *et al.*, 2011), through smart electronic devices (Aliu; Oke, 2023). Table 1 summarizes the most widely used and recognized digital technologies in the construction industry. This study explores their application in the Brazilian construction industry, the project phases in which they are applied, and the factors influencing their adoption.

Table 1**- Summary of main DT applied in the construction industry**

DT	Brief description
Big Data	The process entails collecting, processing, and analyzing large datasets to address key questions and support decision-making.
Blockchain	A technology that records all events and transactions of validated, encrypted digital data, executed and shared among participants, ensuring the security of the involved data.
Cloud Computing	Cloud computing is the capacity to store, process, and retrieve data in the cloud
Unmanned Aerial Vehicles (UAV)	A remotely controlled aerial vehicle, equipped or not with sensors, to supervise, assess, and inspect ongoing operations.
Digital Twin	A digital or simulated representation of a real-world physical process or system, updated with specific frequency and accuracy, and employed for simulate, monitor, and optimize performance
3D Printing	Also known as additive manufacturing, 3D Printing is a technology used to produce 3D objects by layering materials such as concrete, polymers, or other materials
Artificial Intelligence	The ability of machines and technology to make decisions and solve complex problems using algorithms based on human intelligence
Internet of Things (IoT)	IoT is the interconnected network of physical objects with sensors, software, and network connectivity
Building Information Modeling (BIM)	BIM can be defined as a technology and methodology for managing the design and data of a building in digital format throughout its life cycle, using an intelligent information model
Augmented Reality (AR)	Technologies that incorporate virtual elements and computer-generated objects into a physical or real environment through visualization devices.
Virtual Reality (VR)	The use of a computer-generated environment or an immersive simulation in which users are placed within virtual scenarios that can enhance comprehension among construction project stakeholders and elevate their ability to complete projects successfully
Robotics	The use of programmed machines to autonomously interact with objects and perform tasks with greater safety and efficiency.
Sensors	The use of sensory devices to capture real-time information, which is then processed by algorithms and analytical tools to execute actions and make decisions in real time.
Wearables	Smart electronic devices incorporated into clothing and/or worn by the user, detecting behavior and movement while processing this data

Source: based on Shawhney, Riley and Irizarry (2020).

As the construction industry lags behind other industries in the adoption of new technologies (Hwang; Ngo; Teo, 2022), many studies have sought to understand the factors preventing and driving DT adoption around the world.

In China, Wang *et al.* (2024) grouped the main barriers into three categories:

(a) lack of laws and regulations;

(b) lack of support and leadership (LSL); and

(c) lack of resources and professionals (LRP).

In turn, Zhang *et al.* (2023) identified the following as prominent barriers:

(a) data fragmentation;

(b) lack of core technology;

(c) weak digital infrastructure allocation;

(d) lack of technical personnel; and

(e) lack of technical standards.

In New Zealand, Chen *et al.* (2024) highlight the following eight barriers:

(a) data and information security;

(b) ethical and privacy concerns;

(c) industry standards;

(d) legal environment;

(e) lack of interest;

(f) lending restrictions;

(g) no financial need/drive; and

(h) lack of awareness.

These eight critical barriers were further classified into technical, environmental, and social dimensions to determine the major constructs that hinder DTs adoption.

Dolla, Jain and Kumar Delhi (2023) explores the Strategies for digital transformation in construction projects in India. The authors proposed that the top four strategies are stakeholder integration, process re-engineering, training activities, and the need to generate federated data. These strategies arise from empirical data and are based on the challenges faced by practitioners in adopting DT. Also in India, Bajpai and Misra (2023) showed the importance of stakeholder perceived benefit associated with digitalization.

In Malaysia, Almatari, Chan and Masrom (2024) identified the main factors influencing the adoption of Construction IR 4.0 technologies as:

(a) high implementation costs;

(b) hesitation to adopt technologies;

(c) lack of standards;

(d) legal and contractual uncertainty; and

(e) complexity.

In Nigeria, Oke, Aliu and Onajite (2024) grouped the barriers in five categories: organizational, management, technical, regulatory, and economic.

In Singapore, Hwang, Ngo and Teo (2022) identified the top challenges faced by practitioners in adopting smart technologies a:

(a) data and information sharing;

(b) regulatory compliance; and

(c) data ownership.

The most effective strategies to address these challenges include training a skilled construction workforce, providing government incentives, and implementing communication and change management strategies.

In summary, these studies show that differences in adoption rates depend on many factors such as professional profiles, organizational aspects (Aliu; Oke, 2023; Dolla; Jain; Kumar Delhi, 2023), and the business environment (Chen *et al.*, 2022). The literature also underscores the connections between Lean Construction (LC) and DT use (Altan; Işık, 2024; Sacks *et al.*, 2020).

Particularly in Brazil, there is a lack of information on the current use of DT in peer-reviewed journals, indicating that research on the topic is still in its early stages. As mentioned in the introduction, Tanaka *et al.* (2024) conclude that the Brazilian construction industry lags behind other economic sectors in terms of digital maturity. Fernandes and Costa (2024) developed a conceptual model for measuring the maturity of an intelligent construction environment. As limitation, the authors do not calculate the maturity of the companies. Only two technical reports conducted by BIM Fórum Brasil in partnership with the Federal Council of Engineering and Agronomy (CONFEA) and the Council of Architecture and Urbanism (CAU/BR) provide a broad diagnostic of the use of DT in the Brazilian construction industry (BIM Fórum Brasil, 2022a, 2022b). Despite this, there are no studies addressing the factors that influence the use of DT.

Finally, another limitation of the reviewed literature is the lack of theoretical frameworks behind their categorization. Only the study by Bajpai and Misra (2023) adopts the Technology Acceptance Model (TAM) as a theoretical foundation. To fill this gap, this study adopts the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM) to explain the underlying mechanisms of technology adoption, as described in the next subsection.

Underlying mechanisms of technology adoption based on the combined TPB-TAM

According to Theory of Planned Behavior (TPB), the intention to perform a behavior predicts a behavior (Ajzen, 1991; Fishbein; Ajzen, 2015), such as adopting digital technologies (DTs). Based on TPB, this intention is influenced by three factors: attitude toward behavior, subjective norms, and perceived behavioral control. Attitude toward the behavior refers to an individual's positive or negative evaluation of performing it. Subjective norms represent the social pressure perceived by an individual to engage in or refrain from a behavior. Perceived behavioral control relates to the perceived ease or difficulty of performing the behavior. This control encompasses abilities, opportunities, and available information, representing an individual's confidence in their ability to perform the behavior. Actual Behavioral Control also influences behavior. It refers to the extent to which a person has the skills, resources, and other prerequisites needed to carry it out, i.e., the current capacity to perform it. The central hypothesis of TPB states that the more favorable these factors are, the higher the propensity to perform the behavior. Thus, the behavior is guided by intention, which acts as a mediator between the influence of attitude, subjective norm, and perceived behavioral control.

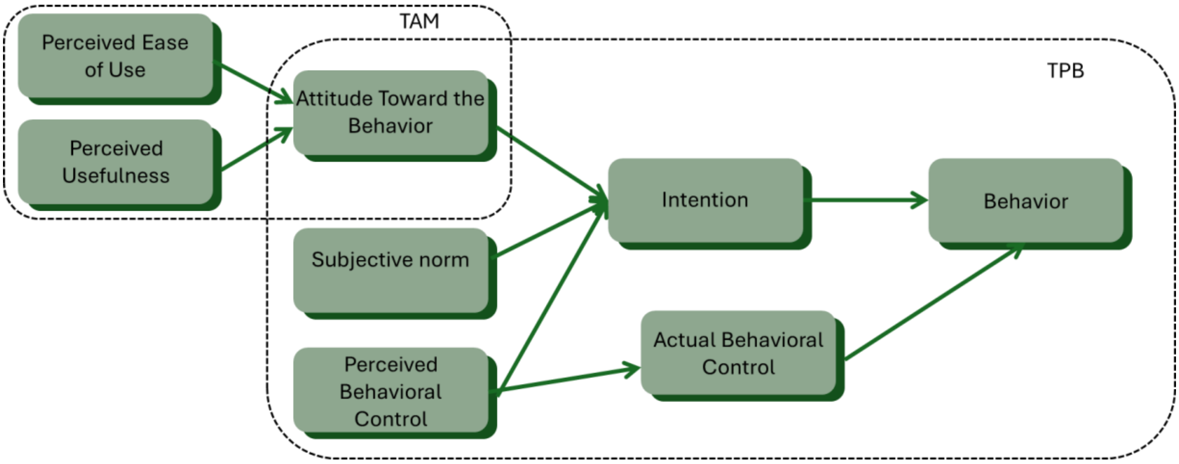
Moreover, since the behavior investigated is related to technology this study extends TPB by incorporating the Technology Acceptance Model (TAM) (Davis, 1989), as proposed by Taylor and Todd (1995). According to TAM, behavioral intention is a key factor driving technology usage and is determined by Perceived Usefulness and Ease of Use. In other words, TAM posits that the more useful and easier a technology is perceived to be, the more favorable an individual’s attitude toward its use. The concept of attitude in TAM is analogous to attitude toward the behavior in TPB. Again, this attitude influences intention, which in turn acts as a mediator for actual technology usage. The combined TAM-TPB constructs are depicted in Figure 1.

Building on these ideas, the factors that influence the use of technologies were organized into a theoretical model, as detailed in the next subsection.

Theoretical model for the propensity to use DT in the construction industry

The combined TAM-TPB model was used in this study to categorize the factors identified in the literature review and to propose a theoretical model explaining the propensity (intention) to use DT in the Construction Industry, as detailed in the following subsections.

Figure 1 – **Combined TAM-TPB model**



Source: based on Davis (1989), Ajzen (1991) and Taylor and Todd (1995).

Perceived ease of use, perceived usefulness and attitude toward behavior of using DT

Perceived Ease of Use and Perceived Usefulness are important predictors of attitude. This is also valid in the context of use of DT in the Construction Industry (CI). Regarding the perceived ease of use, some studies revealed that complexity and difficulty to use are barriers to BIM adoption (Wong *et al.*, 2025). Similarly, Almatari, Chan and Masrom (2024) consider complexity as an inhibiting factor for Industrial revolution 4.0 adoption.

In turn, perceived usefulness is a key driver factor (Bajpai; Misra, 2023). The literature highlights several benefits of DT application in the construction industry, including improvements in productivity (Chen *et al.*, 2022; Oke *et al.*, 2024a), health and safety on-site (Chen *et al.*, 2022), decision-making (Aliu; Oke, 2023; Oke *et al.*, 2024b), cost reduction (Oke *et al.*, 2024b), agility in error detection (Elghaish *et al.*, 2021), and quality of the final product (Bajpai; Misra, 2023), among other benefits. According to Ernstsen *et al.* (2021), there are three emergent visions for digital transformation of the sector: efficient construction, user-data-driven built environment, and value-driven computational design.

Perceived Ease of Use and Perceived Usefulness play a critical role in shaping Attitude Toward the Behavior of Using DT, as Construction Industry professionals are generally considered conservative in adopting innovative technologies (Hofman; Vries; Kaa, 2022). This is in line with the awareness of professionals regarding the uses and benefits of DT showed in technical reports conducted by BIM Fórum Brasil (BIM Fórum Brasil, 2022b, 2022a). Furthermore, they show that professionals demonstrate interest in the subject and recognize the need for guidance and training. This suggests that they are aware of the challenges and the importance of taking action to overcome them.

Based on these considerations, this study formulates the following hypotheses:

H1a. Perceived Ease of Use has a significant positive effect on Attitude Toward the Behavior of Using DT.

H1b. Perceived Usefulness has a significant positive effect on Attitude Toward the Behavior of Using DT.

Attitude toward behavior, subjective norm, and intention

Attitude Toward Behavior and Subjective Norm are important predictors of Intention. As previously discussed, the Attitude Toward Behavior can be positive or negative, and is influenced by Perceived Ease of Use and Perceived Usefulness. The more favorable the Attitude Toward Behavior, the higher the Intention to perform the behavior.

In turn, subjective norm refers to perceived social pressure, i.e., social norms determine what is acceptable or permissible behavior within a group or society (Fishbein; Ajzen, 2015). In this study, the subjective norms related to the use of DT are conceptualized as the social pressure stemming from the business environment, the organization's commitment to adopt DT, and its management philosophy.

The business environment includes government incentives, regulations and regulatory frameworks. The lack of government incentive, such as legislation demanding the use, promoting financing, and dissemination, can be a barrier to adoption DT (Aliu; Oke, 2023; Bajpai; Misra, 2023; Hwang; Ngo; Teo, 2022; Zhang *et al.*, 2023). Additionally, the lack of established standards (Almatari; Chan; Masrom, 2024; Hwang; Ngo; Teo, 2022; Oke; Aliu; Onajite, 2024), and the lack of data security and data protection (Hwang; Ngo; Teo, 2022; Oke; Aliu; Onajite, 2024) are barriers. The organizations' commitment to adopt DT, referred to here as Organization Aspects, encompass various factors, including the existence of a strategic plan for DT implementation (Aliu; Oke, 2023; Dolla; Jain; Kumar Delhi, 2023), awareness of DT benefits at organizational level (Chen *et al.*, 2024), leadership engagement in DT adoption (Bajpai; Misra, 2023; Hwang; Ngo; Teo, 2022; Oke; Aliu; Onajite, 2024; Zhang *et al.*, 2023), and the presence of a learning culture within the organization (Oke; Aliu; Onajite, 2024).

Finally, the literature highlights strong connections between Lean Construction (LC) and DT use (Altan; Işık, 2024; Sacks *et al.*, 2020). According to Sacks *et al.* (2020), the combination of LC and DT is a suitable strategy to improve operational results. As construction projects become more complex, LC-based projects require effective communication systems supported by Information and Communication Technologies (ICTs) to manage the increasing availability of data for decision-making. Therefore, many benefits of adopting DT align with LC principles (Altan; Işık, 2024). The fundamental principles considered in this study were:

(a) improving workflow;

(b) reducing non-value-adding activities;

(c) minimizing process variability; and

(d) identifying waste (overproduction, waiting, transportation, rework, among others).

These principles also compose the theoretical model.

Based on these considerations, this study formulates the following hypotheses:

H1. Positive Attitude Toward Behavior has a significant positive effect on Intention to Using DT.

H2. Business Environment has a significant negative effect on Intention to Using DT.

H3. Organizational Aspects have a significant positive effect on Intention to Using DT.

H4. Lean Construction principles have a significant positive effect on Intention to Using DT.

Perceived behavioral control, actual behavioral control and intention

According to TPB (Ajzen, 1991; Fishbein; Ajzen, 2015), beyond a favorable attitude and perceiving social pressure, the Perceived Behavioral Control is also important for forming an intention to perform a behavior. The Perceived Behavioral Control is related to Actual Behavioral Control, as it refers to the extent to which a person has the skills, resources, and other prerequisites needed to carry it out, i.e., the current capacity to perform it.

In this study, the Perceived Behavioral Control was conceptualized as the Necessary Resources (NR) to Using DT. This generally encompasses the sunk investments, particularly costs associated with implementation and operation (Chen *et al.*, 2024; Hwang; Ngo; Teo, 2022; Oke *et al.*, 2024a; Oke; Aliu; Onajite, 2024), the necessity for adequate infrastructure (Hwang *et al.*, 2021; Bajpai; Misra, 2023), necessity for data security (Hwang; Ngo; Teo, 2022; Bajpai; Misra, 2023; Chen *et al.*, 2024; Oke; Aliu; Onajite, 2024), and the need for skilled labor (Aghimien *et al.*, 2022; Hwang; Ngo; Teo, 2022; Oke *et al.*, 2024a, 2024b). In turn, Actual Behavioral Control was conceptualized as Current Capacity (CC), encompassing the skills necessary to use DT (Hwang; Ngo; Teo, 2022; Aghimien *et al.*, 2022; Oke *et al.*, 2024a, 2024b) by the individual himself (self-efficacy), by other professionals around him and by the presence of experts in the sector.

Based on these considerations, this study formulates the following hypotheses:

H5. Necessary Resources has a significant negative effect on Intention to Using DT.

H6. Necessary Resources Control has a significant negative effect on Current Capacity.

Intention, actual behavioral control and behavior

Finally, to complete the theoretical model, it is necessary to clarify the relationship between Intention, Actual Behavioral Control and Behavior. According to TPB (Ajzen, 1991; Fishbein; Ajzen, 2015), both Intention and Actual Behavioral Control influence Behavior. The Actual Behavioral Control was described in the last subsection and renamed by Current Capacity. To capture the Intention, three proxies were used: willingness to use; intention to expand the actual use to other phases of the project; and intention to adopt new technologies (Fishbein; Ajzen, 2015).

Based on these considerations, this study formulates the following hypotheses:

H7. Intention to Using DT has a significant positive effect on Using DT.

H8. Current Capacity has a significant positive effect on Using DT.

Building on these ideas, Figure 2 present the preliminary Theoretical Model developed.

The theoretical model consists of 36 variables, grouped into 10 constructs, and 10 hypotheses. The 36 variables are shown in grey boxes, which are linked to the green boxes representing the 10 constructs. The 10 hypotheses are labeled as H1a(+) to H8(+), where (+) indicates a positive effect and (–) indicates a negative effect between constructs.

In summary, Attitude Toward Use, combined with Business Environment, Organizational Aspects, Lean Construction, and Necessary Resources, influences the Intention to use DT. Additionally, Necessary Resources also influence the Currente Capacity. Finally, Behavioral Intention to use DT, together with Current Capacity, influences the Use of DT, which is the model's dependent variable.

Method

This study followed four steps, as illustrated in Figure 3, which presents the quantitative research approach employed and is detailed in the next subsections.

Figure 2 - **Theoretical Model to explain the use of DT in the construction industry**

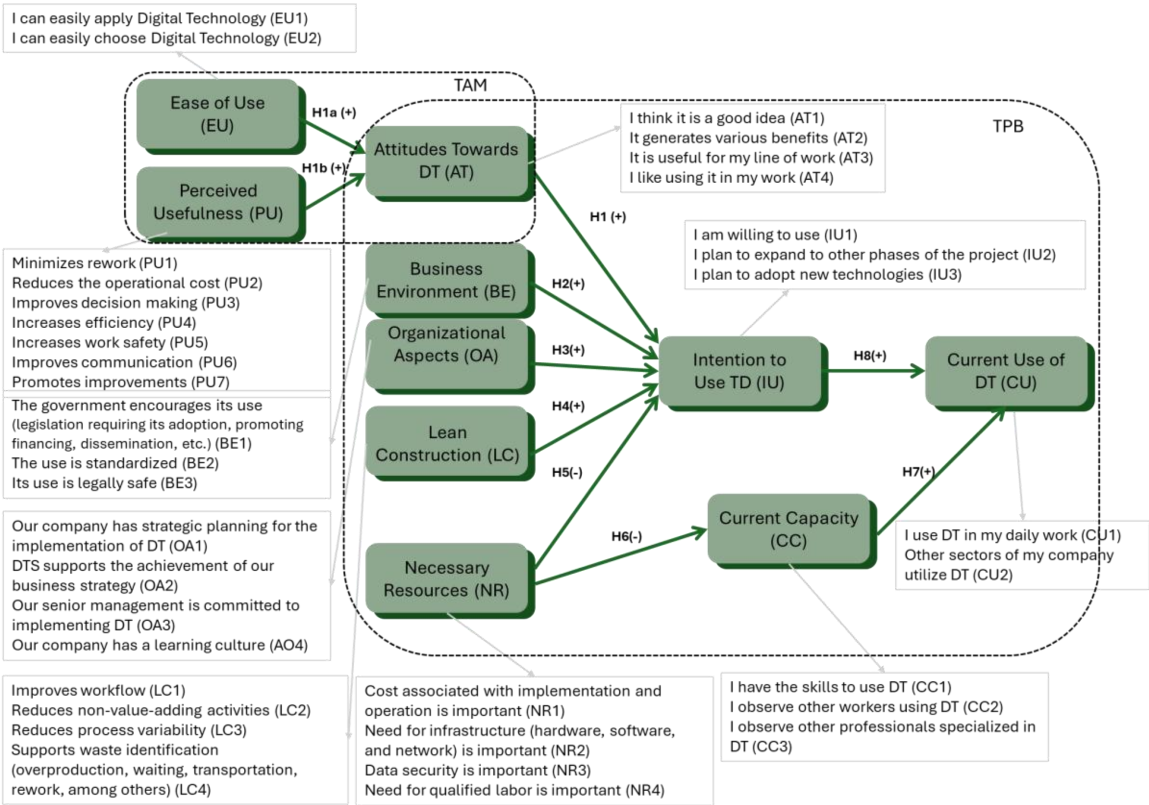
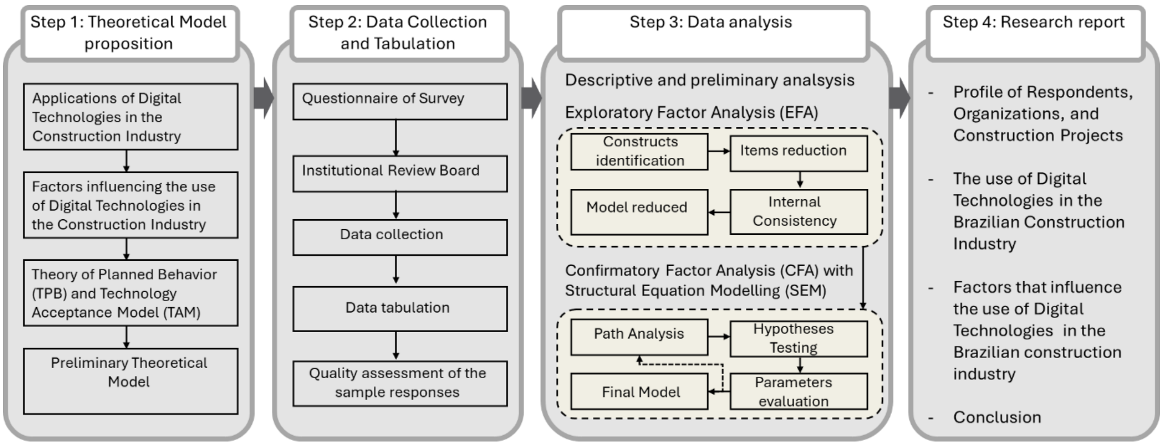


Figure 3 - **Research procedures**



Step 1: Theoretical Model proposition based on literature review

In the first step, a Theoretical Model was proposed based on a literature review. The review was conducted in Scopus and Web of Science databases in December 2023, specifically targeting journals and articles published until 2023. The query string used was: TITLE-ABS-KEY ((construction AND "digital technology") AND (adoption OR implementation OR challenges OR barriers OR advantages OR benefits)). The following filters were applied: only papers and reviews published in journals; papers in English, Spanish, and Portuguese; documents published until 2023; and subject area restricted to Engineering. Further, the adherence of works to the research aims was verified through a screening process by reading the title, abstract, and full text, and removed the duplicated documents.

The documents were comprehensively reviewed to identify the main technologies used in the Construction Industry, the project phases in which they are applied, and the factors influencing their adoption. These elements were structured under the conceptual frameworks of Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM). TPB explains the underlying mechanisms of human behavioral engagement, while TAM addresses the specificity of behavior when it involves digital technology. As an outcome, this phase provides the preliminary theoretical model presented in the literature review and research hypothesis.

Step 2: Data collection and tabulation

In the second step, data collection and tabulation were performed. Before that, a questionnaire was outlined, based on the preliminary theoretical model proposed. The questionnaire consisted of three sections. The first section included 10 questions to profile the respondents. The second section contained 12 questions to characterize the companies and construction projects. Additionally, it explored the use of DTs, covering the 14 technologies presented in the literature review and research hypothesis. The third and final section comprised 10-point Likert scale statements, where respondents indicated their degree of agreement or disagreement with 36 variables, as showed in Figure 2. “I can easily apply Digital Technology” is one of the assertions used to evaluate factors influencing the use of DT in the Construction Industry.

The questionnaire underwent two rounds of pretesting, each involving three civil engineers. The first round included three civil engineers in Technical Director positions, while the second round involved three engineers in operational roles. This approach ensured coverage of different respondent profiles, ranging from operational to strategic levels. They responded to the questionnaire and were asked to review the comprehensiveness of the identified factors and variables, as well as the quality and readability of the inquiries. In the first round, participants reported that the format of the questions was repetitive and tiring, suggesting simplification. Therefore, the wording of the questionnaire was simplified, and a second round of validation was conducted. No further concerns of that kind were raised. The average time required to complete the questionnaire was reduced from 17 to 10 minutes, demonstrating the effectiveness of the simplification. All participants considered that the variables and factors identified in the literature review were comprehensive and reflected the main preventing factors or can drive the use of DT in the construction industry.

The final questionnaire, available as supplementary material at [omitted– and attached for blind review], was submitted to and approved by an institutional review board, the Research Committee of the Federal University of Ceará (CEP/UFC/PROPESQ). It is available on Plataforma Brasil under the Proof of Application for Ethical Review number CAAE 81676524.2.0000.5054.

The questionnaire was distributed to professionals in the Brazilian Construction Industry, and a non-probabilistic sample was obtained (Hair *et al.*, 2009), using snowball strategy. The researchers leveraged their personal contacts and social media to disseminate the survey. The respondents were encouraged to share the invitation with their social media networks. It is estimated that this yielded around 1000 professionals, from whom 154 responses were obtained (15.4%). These responses underwent initial screening to check for inconsistencies in the data, resulting in the exclusion of six questionnaires. The remaining responses were subjected to basic statistical quality checks, following four steps:

(a) checking for missing values in all cases;

(b) checking for missing values in all variables;

(c) identifying disengaged responses; and

(d) identifying extreme values.

After these procedures, the final dataset consisted of 144 valid responses. This sample partially meets the assumptions for conducting a factor analysis (Hair *et al.*, 2009). Moreover, this is compatible with other studies with similar quantitative research approach, such as Nguyen *et al.* (2024), with a sample of 136, and Olanrewaju *et al.* (2022), with a sample of 90 valid responses.

Step 3: data analysis

In the third step, the data analysis was conducted in three stages:

(a) descriptive and preliminary analysis;

(b) Exploratory Factor Analysis (EFA); and

(c) Confirmatory Factor Analysis (CFA) with Structural Equation Modelling (SEM).

Descriptive and preliminary analysis

Descriptive statistics were initially used to profile the respondents, their organizations, and their construction projects. Moreover, skewness and kurtosis statistics were analyzed to assess the normality of multivariate data for each variable. Cutoff values used ranged frpm 3 to 10 (Hair *et al.*, 2009). Additionally, the Kolmogorov-Smirnov (KS) test was employed to confirm the null hypothesis of normality, considering a p-value > 0.05 for any significance level. Pearson's correlation coefficient (*r*) was used before proceeding with the factorial analysis. For this analysis, the statistical significance of correlations must be between 0.2 and 0.9 (Costa, 2011), and most values should be significant and above 0.3 (Hair *et al.*, 2009) as criteria for conducting factorial analysis.

Overall, the level of concordance with the proposed assertions in the scale items was moderate, with 58% of responses above 7, ranging from 11.1% (BE2) to 87.5% (AT1). The most critical skewness and kurtosis values were -2.403 and 5.742, respectively, for AT2. These values satisfy the assumption adopted, given the cutoff range of 3 to 10 (Hair *et al.*, 2009). All KS test results led to the rejection of the null hypothesis (p-value = 0.000) at the 1% significance level. The statistical significance of all correlations met the specified assumption, with cutoff values between 0.2 and 0.9 (Costa, 2011) and correlation values above 0.3 (Hair *et al.*, 2009). The lowest correlation value was 0.458 between BE1 and BE3, while the highest was 0.947 between AT1 and AT2.

In summary, the result of the assumption checks for sample response distribution, normality, and correlations met the criteria to proceed with Exploratory Factor Analysis (EFA), as detailed in the next subsection.

Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) was conducted using IBM SPSS Statistics 21. The adequacy of the correlation matrix was verified through Bartlett's statistic (p-value = 0.000), the Kaiser-Meyer-Olkin (KMO > 0.5) test, and the measure of sampling adequacy (MSA > 0.5) (Hair *et al.*, 2009). According to Fávero *et al.* (2009), Bartlett's test evaluates whether the correlation matrix is an identity matrix, which would indicate that correlations between variables are null, making them unsuitable for factor analysis. Meanwhile, the KMO test assesses the adequacy of the sample based on partial correlations between variables, where higher values indicate a better sample, with a cutoff above 0.5.

EFA was conducted using the maximum likelihood extraction method with varimax rotation to achieve factor simplicity (Hair *et al.*, 2009). The number of factors was determined based on explained variance using eigenvalues. According to this method, only factors that have latent roots greater than 1 are considered significant, while others were discarded. To identify inappropriate items in factor analysis, the values of communalities (>0.50) and cross-factor loadings (>0.70) were examined (Hair *et al.*, 2009).

Finally internal scale reliability was assessed using Cronbach's alpha [$\alpha > 0.8$ considered 'almost perfect' (Hair *et al.*, 2009)] and McDonald's omega (ω>0,70) (McDonald, 2011). McDonald's omega is currently regarded as a more robust measure of internal consistency than Cronbach's alpha (Sijtsma; Pfadt, 2021). This index was calculated using Jamovi 2.2.5.

In summary, since the assumptions regarding sample adequacy were satisfied, EFA was performed to refine the constructs and variables of the preliminary model. After confirming that the internal scale reliability of the reduced model was satisfactory, Confirmatory Factor Analysis (CFA) with Structural Equation Modelling (SEM) was conducted, as detailed in the next subsection.

Confirmatory Factor Analysis (CFA) with Structural Equation Modelling (SEM)

Confirmatory Factor Analysis (CFA) with Structural Equation Modelling (SEM) was conducted using IBM SPSS Statistics 21 with IBM SPSS® Amos. Like EFA, CFA was also conducted using the maximum likelihood extraction method in combination with a varimax rotation, and the explained variance based on eigenvalues to determine the number of factors. Cronbach's alpha and McDonald's omega were used to evaluate internal scale reliability.

Initially, path analysis was used to evaluate causal models (Hair *et al.*, 2009). To do so, a path diagram illustrating the relationships between all variables of the reduced EFA model was input into IBM SPSS® Amos. Then, the fit measures of the model were calculated, and the hypotheses were tested interactively to achieve a final respecified model. The interactive tests involved adding modification indices, such as covariances between errors, to improve the model fit results.

The main criterion for adjusting the model was $\chi 2$ statistic with cut-off criteria of p-value > 0.05. Additionally, a Critical Ratio (CR) significant at p-value < 0.001 for the hypothesis of adequacy of items to factors (Hair *et al.*, 2009). Low χ^2 values indicate a good fit of the model, but the statistic is highly sensitive to both sample size and model complexity (Costa, 2011). When the model is complex or the sample size is small, as in the case of the present study, it is more likely that the χ^2 test will indicate a poor model fit, even if the model is reasonable. To overcome this limitation, the ratio between the χ^2 value and the model's degrees of freedom (df) was calculated, providing a more accurate assessment of the model fit. This assessment considered χ^2/df < 5 as acceptable (Hair *et al.*, 2009).

Additional fit indices were evaluated, including: Goodness-of-Fit Index (GFI>0.90); Comparative Fit Index (CFI>0.95); Tucker-Lewis Index (TLI>0.90); Normed Fit Index (NFI>0.90); Root Mean Square Error of Approximation (RMSEA<0.009); and the Standardized Root Mean Square Residual (SRMR<0.08) (Hair *et al.*, 2009).

Based on Costa (2011), these measures are described next. TLI and CFI are incremental fit measures that compare the specified model with a null model and a saturated model, helping to assess how well the proposed model represents the sample data. RMSEA is an absolute fit index that measures the average discrepancy between the specified model and the observed data, evaluating whether a model fits the population reasonably well. SRMR, on the other hand, is a global fit measure that evaluates the difference between the observed correlations and the correlations estimated by the model. In other words, it assesses the degree of discrepancy between predicted and actual correlations, providing insight into how well the confirmatory factor analysis model fits the sample data.

In summary, after an interactive process of model adjustment, regression coefficients, and hypothesis testing, a final, respecified model was empirically validated.

Step 4

Finally, in the fourth and final step, the research report is outlined. This involved preparing tables and illustrations containing the tests results, along with a discussion of the research findings and their implications, as presented in the next section.

Results and discussion

In this section, first, a characterization of respondents, their organizations, and their construction projects is presented. Second, an overview of the current state of DT use in the Brazilian construction industry was provided, identifying the construction phases in which these technologies are used. The third part of this section details the results of the tests conducted to refine and validate the theoretical model. Finally, the fourth part discusses these results in detail, and their implications.

Profile of respondents, organizations, and construction projects

The collected data include responses from 144 construction industry professionals across 14 of Brazil's 26 states, as shown in Figure 4.

A significant portion of these respondents (47%) were from the state of Ceará, which requires attention in the analysis due to potential sample bias. Regarding gender, most respondents are male (72%). The most representative age group ranged from 20 to 29 years old (41%), with 68% of all participants up to 40 years old.

Most respondents are civil engineers (90%), followed by architects (5%) and other types of engineers (electrical, industrial production, and mechanical) (5%). Additionally, 61% of the respondents had more than 5 years of experience, with the largest group having between 1 and 5 years of experience (35%). Regarding job roles, 47% of the respondents worked at the operational level, 35% at the strategic level, and 18% at the tactical level. Moreover, these respondents primarily work in on-site building execution (46%) and building design (33%). Most of the respondents indicated that they are only marginally familiar with DT (57%), while 78% indicated that they are more or less familiar with lean construction.

Table 2 presents the sizes and ages of companies.

Respondents' companies were predominantly medium-sized, representing 26% of the total, which is slightly higher than the average representation of 20% across all company sizes. The most represented company age group was 1 to 5 years, accounting for 37% of the total. Furthermore, 69% of all companies had been established for 10 or more years.

Table 3 presents the types and sizes of construction projects.

Figure 4 – **Distribution of responses by Brazilian states**

Legend: •1 to •44; 0 responses in the state (white) and 99 responses in the state (black).

Table 2 – **Sizes and ages of companies**

Size of Companies	Age of Companies						
	up to 1	**1 to 5**	**6 to 10**	**11 to 20**	**Above 20**	**Total by size**	**% by size**
Sole proprietor	6	15	4	4	2	31	**21.5**
Micro-enterprise	2	16	5	3	0	26	**18.1**
Small company	5	14	5	6	2	32	**22.2**
Medium company	3	5	12	7	10	37	**25.7**
Large company	3	4	1	3	7	18	**12.5**
Total by age	**19**	**54**	**27**	**23**	**21**	**144**	**100**
% by age	**13.19**	**37.5**	**18.7**	**16**	**14.6**	**100**	

Table 3 – **Type and size of projects**

Type of projects	Size of projects						
	Micro	**Small**	**Medium**	**Large**	**Mega**	**Total**	**% by type**
High-income residential buildings	10	19	11	17	8	**65**	**15.8**
Middle-income residential buildings	20	23	16	13	6	**78**	**18.9**
Low-income residential buildings	13	14	4	10	0	**41**	**9.9**
Commercial buildings	17	21	13	14	7	**72**	**17.5**
Industrial buildings	3	6	9	14	7	**39**	**9.5**
Public buildings (government facilities)	3	6	16	13	1	**39**	**9.5**
Public buildings (infrastructure)	4	4	11	19	8	**46**	**11.2**
Public buildings (social housing)	1	2	4	12	0	**19**	**4.6**
Other	**0**	**2**	**3**	**2**	**6**	**13**	**3.2**
Total	**26**	**33**	**30**	**37**	**18**	**144**	**100**
% by size	**18.06**	**22.92**	**20.83**	**25.7**	**12,5**	**100**	**-**

Regarding construction projects, the majority are large-scale (25.7%). In terms of type, middle-income residential buildings predominate at 18.9%, followed by commercial buildings at 17.5% and high-income residential buildings at 15.8%. The category with the lowest representation was “Others”, which included private construction (infrastructure), hospital sector, historical heritage, logistics, solar power plants, energy and mining.

The use of Digital Technologies (DT) in the Brazilian construction industry

Initially, it is worth noting that 87% of the 144 respondents use DT in their daily work. Among them, 57% use up to 4 of the 14 DTs investigated, while 2 respondents reported using 10 DTs. Figure 5 shows the percentage of use for each DT among the 144 professionals.

It is worth noting that 75% of respondents use BIM, followed by Cloud Computing (66%), UAVs (44%), and Virtual Reality (43%). On the other hand, Wearables, Robotics, and Blockchain, each with 6%, were the least used DTs.

The phases of the construction project lifecycle where these DTs are applied were also explored, as shown in Figure 6. In this analysis, it is worth noting that, for each construction project phase, we can see the number of respondents who confirmed the use of a specific DT. In the last column, we display the number of respondents who stated that they do not use such technology. Since respondents were free to select multiple technologies and phases, the sum of each column does not match the total number of respondents.

It is worth noting that Design/Feasibility, Work Execution, and Construction Management phases are the only ones in which all investigated DTs are applied by at least one respondent. For instance, one respondent reported using Wearables in the Construction Management phase, while another reported using them in the Real Estate phase (including purchase, sale, and rental). In contrast, the Demolition/Renovation/ Refurbishment phase had the fewest types of DTs applied.

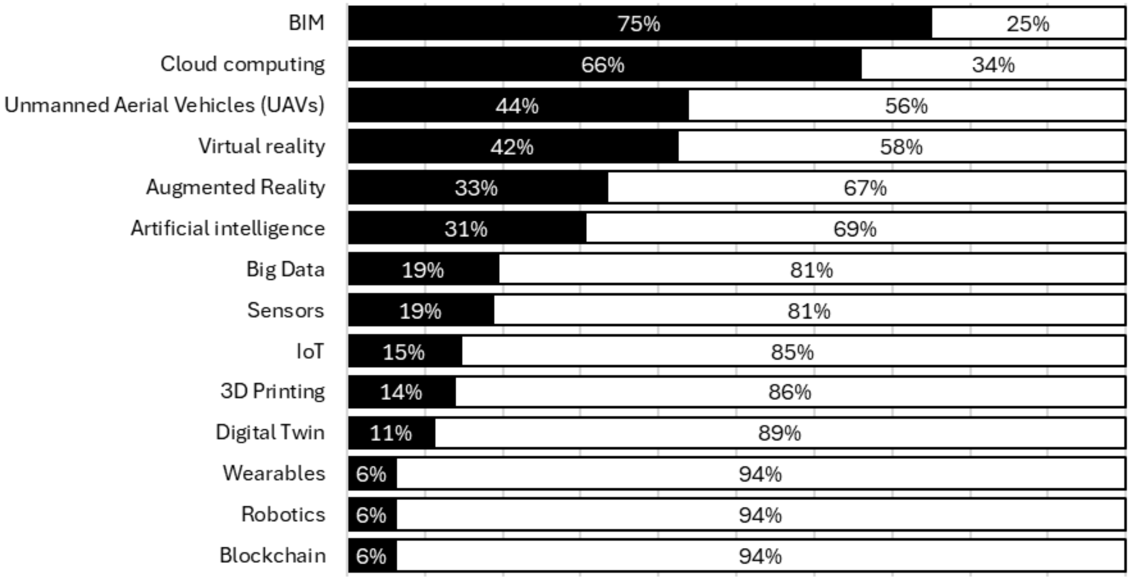
When examining the phases together with DTs application, we observe that BIM is the most widely used in the Design/Feasibility phase. Notably, 39 respondents reported employing Cloud Computing in the purchasing process, making it the most frequently used technology across all other phases. Conversely, Wearables are the least used in all phases, followed by Robotics, 3D Printing, and Sensors. Most respondents reported using these technologies for up to 10 years.

Analysis of theoretical model

Preliminary analysis

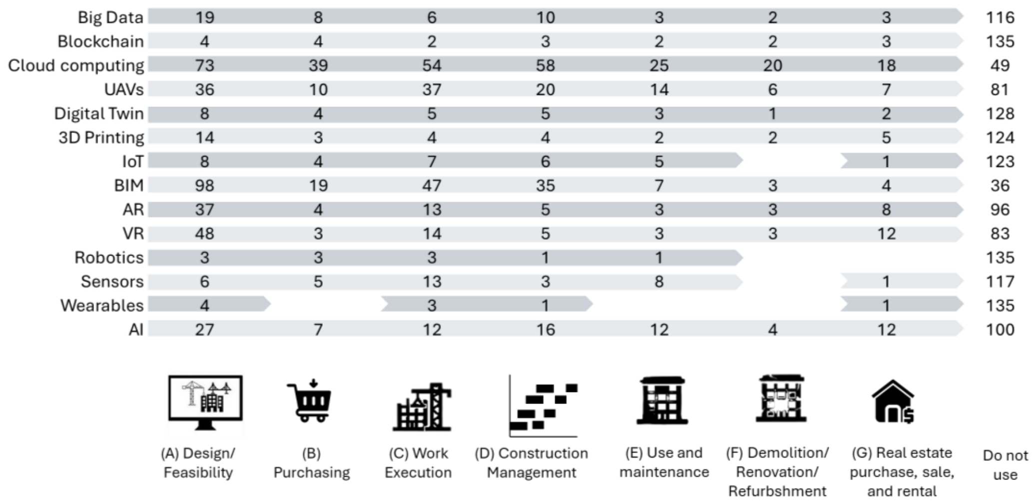
Initially, for each construct of the Theoretical Model, a descriptive analysis was conducted, including the percentage of responses assigned to each scale point, the mean score, standard deviation, and coefficient of variation. Furthermore, to assess the normality of the research data, we examined skewness, kurtosis, and the Kolmogorov-Smirnov test, along with a correlation analysis. In summary, these statistics indicate the adequacy of the variables for further analysis.

Figure 5 - **Percentage of use for each technology**



Legend: ■ % of respondents who use the DT; □ % of respondents who do not use the DT.

Figure 6 - **Use of DT by phase of construction Project lifecycle**



In the correlation analysis, all variables were found to be statistically significant, with correlations above 0.3 at the 1% significance level. These results validate the suitability of the variables to proceed with the Exploratory Factor Analysis (EFA), as presented in the following section.

Exploratory Factor Analysis (EFA)

Bartlett's test of sphericity yielded good results ($p < 0.001$), and all KMO values exceeded 0.5, ranging from 0.500 (Ease of Use and Current Use) to 0.922 (Perceived Usefulness). All MSA values surpassed the minimum threshold (MSA > 0.5), ranging from 0.500 for variables related to Ease of Use to 0.940 for PU2 within the Perceived Usefulness construct. These results confirm the adequacy of the sampling for all constructs.

Subsequently, factor analysis was conducted for each construct, resulting in the exclusion of constructs Ease of Use and Business Environment due to low communalities among their items. Additionally, the AC1 variable from the Current Capacity construct was excluded due to its low communality (0.475).

Confirmatory factorial analysis with structural equation modelling

Table 4 provides a summary of the main indices of CFA by construct.

These results confirm the adequacy of the model, and a Structural Equation Modeling (SEM) was subsequently conducted, as summarized in Table 5.

Hypotheses H1b and H1 were supported at 0.1% significance level, with regression coefficients of 0.797 and 0.378, respectively. H3 was also supported at 5% significance level, with a regression coefficient of 0.183. In contrast, H4 was not supported, indicating that it is not a determining factor. H5 and H6 were supported at 0.1% level. Although a negative influence was expected for both hypotheses, the results suggest that, despite the barriers to implementing DTs identified under Necessary Resources, professionals recognize these challenges. H7 was supported at 0.1% level, with a regression coefficient of 0.579, while H8 was supported at 5% level ($p < 0.05$), despite its low correlation (0.177). The model confirms that Intention to Use, associated with hypotheses H1, H3, H4, and H5, increases the propensity for the Current Use of Digital Technologies, reinforcing the fundamental concept underlying the model's development.

Thus, Figure 7 presents a respecified model.

The final model was tested for reliability, yielding excellent results for both Cronbach's alpha ($\alpha = 0.954$) and McDonald's Omega ($\omega = 0.959$). The KMO value (0.906) and Bartlett's sphericity test were also excellent, confirming the adequacy of the sample. The anti-image correlation matrix values were mostly below 0.7, and the MSA was 0.947, which is also considered excellent. The variance explained was also satisfactory at 73.567%.

Table 4 - **A summary of the main indices of CFA by construct**

Indices/Factors	PU	AT	OA	LC	NR
Number of Rotations	5	2	2	2	1
p-*value*	0.067	0.267	0.776	0.585	0.431
χ^2	17.373	1.230	0.081	0.298	1.681
χ^2/df (<5)	1.737	1.230	0.081	0.298	0.840
GFI (>0.90)	0.966	0.996	1.000	0.999	0.994
CFI (>0.95)	0.994	1.000	1.000	1.000	1.000
RMSEA	0.072	0.040	0.000	0.000	0.000
Lower Factor Loading	0.768 (UP5)	0.706 (AT3)	0.806 (AO4)	0.888 (CE4)	0.810 (RN4)
Lower Communality	0.590 (UP5)	0.550 (AT3)	0.649 (AO4)	0.788 (CE4)	0.656 (RN4)
Lower Critical Ratio	13.124 (UP5)	12.388 (AT1)	13.200 (AO1)	17.097 (CE1)	11.791 (RN3)
Explained Variance (%)	80.735	81.503	81.865	86.765	74.606
Cronbach's alpha (α>0.8)	0.966	0.915	0.946	0.962	0.920
McDonald's omega (ω>0.7)	0.968	0.929	0.947	0.963	0.921

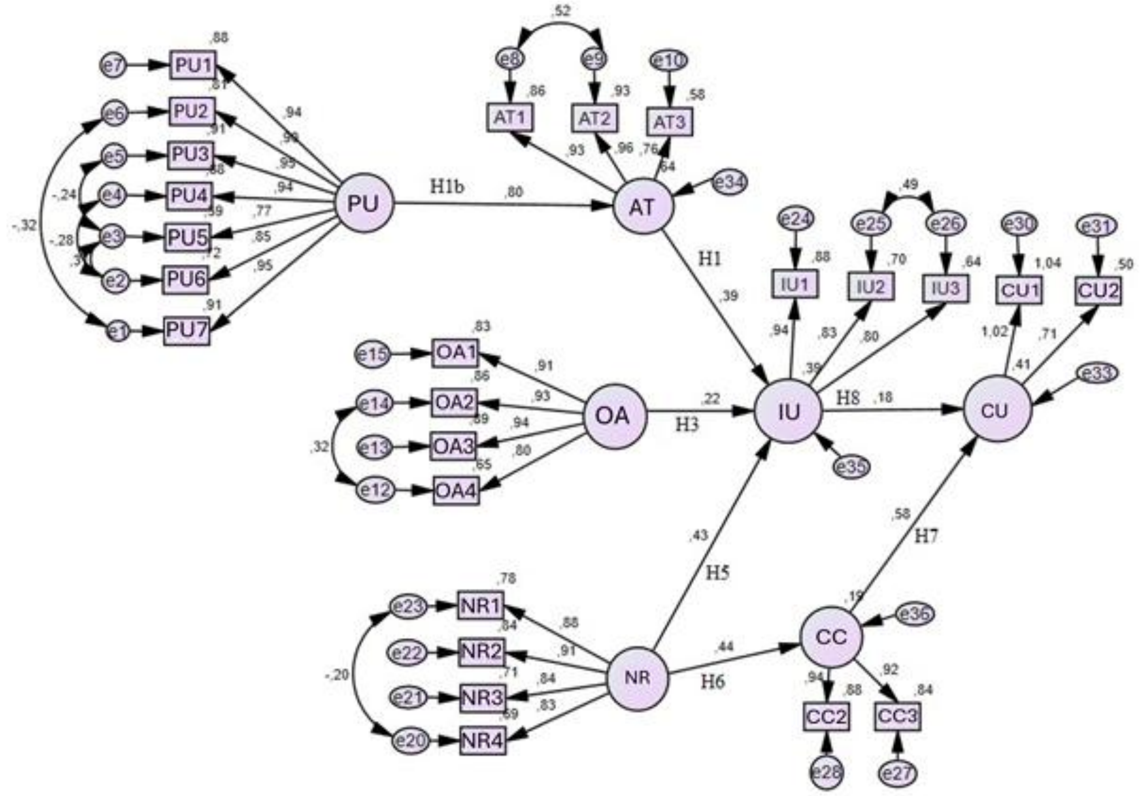
Note: a. Signifcant at 0.001 level.

Table 5 - **Results of the structural equation modeling (SEM)**

Path	SE	p-*value*	Hypothesis	Test
PU→ AT	0.797	***	H1b	Not rejected
AT→ IU	0.378	***	H1	Not rejected
OA→ IU	0.183	0.016	H3	Not rejected
LC→ IU	0.141	0.059	H4	Rejected
NR→ IU	0.399	***	H5	Not rejected
NR→ AC	0.436	***	H6	Not rejected
AC→ AU	0.579	***	H7	Not rejected
IU→ AU	0.177	0.011	H8	Not rejected

Note: ***signifcant at 0.001 level.

Figure 7 - **Confirmatory factor analysis path diagrams of the respecified model**



Among the CFA indicators, the model was not validated and the p-value of the X² statistic was inadequate. Among the adjustment indices, only GFI did not meet the required threshold: X²/GL = 1.998 (<5), GFI = 0.795 (<0.9), CFI = 0.935 (>0.90), RMSEA = 0.084 (>0.08), NFI = 0.879 (<0.90), TLI = 0.925 (>0.9) and SRMR = 0.2938 (>0.08). Despite this, the model was considered well-adjusted in the structural equation analysis, consistent with findings from other studies in the field. For example, Aghimien *et al.* (2022) reported a GFI of 0.805 and deemed their grouped components of their variables suitable as significant factors.

Discussion

Initially, it is important to highlight that the most used technologies were BIM, Cloud Computing, Unmanned Aerial Vehicles and Virtual Reality. This result differs from those of BIM Fórum Brasil (2022a, 2022b), which identified that integrated BIM solutions, Internet of Things, Augmented Reality, Virtual Reality, UAVs and Artificial Intelligence were among the least used. Considering the time gap between these studies, it can be inferred that the adoption of DTs in the Brazilian construction sector has evolved.

Regarding the application phases, the main technologies are integrated into the Design/Feasibility, Construction Management and Execution phases. Since no previous research in the Brazilian context has provided a comprehensive overview of the use of different technologies across various phases, this result represents an original contribution. These findings suggest that the main objectives are predominantly related to improving construction efficiency, aligning with Ernstsen *et al.* (2021). Additionally, they indicate significant opportunities for improvement in the other phases. Technology adoption should be expanded to the Use and Maintenance phase, given its significant impact on users' quality of life.

Regarding the factors influencing the propensity to use DT in the Brazilian construction sector, the model was tested and refined, resulting in a respecified model consisting of 25 variables and 7 constructs.

Constructs Ease of Use (EU), Business Environment (BE) and Lean Construction (LC) were excluded, indicating that they are not perceived as determining factors. Consequently, H1a was refuted, as it addressed two important aspects. The first concerns the complexity of using digital technologies, which arises not only from the technologies themselves but also from their lack of initial development for the sector, which may require significant adaptation. The second aspect relates to the profile of professionals in the sector, who are generally considered conservative regarding the large-scale adoption of innovative technologies (Hofman; Vries; Kaa, 2022). This finding highlights an opportunity for technological development in the industry, particularly through the application of existing technologies to sector-specific needs. A notable example is the incorporation of Solid Modeling, originally developed for the aerospace and mechanical industries, into BIM software (Sacks *et al.*, 2018).

Business Environment, investigated through government incentives, standardization, and data security, does not appear to be perceived as a significant factor by respondents. In other words, these elements do not seem to affect the propensity to use DT in the sector, resulting in the non-confirmation of H2. This finding contradicts the previous literature, which highlights the lack of government incentives (Bajpai; Misra, 2023; Chen *et al.*, 2024; Oke *et al.*, 2023), technical standards and legal security (Oke; Aliu; Onajite, 2024) as key barriers to DT adoption in the sector. These findings suggest that the propensity to adopt DT is primarily an intrinsic phenomenon at both the company and individual levels, reinforcing the influence of Perceived Usefulness, as discussed below.

The results for Lean Construction indicate that, regardless of these aspects of production organization, respondents have been using DT, thus refuting H4. This finding may stem from limitations in fully leveraging the potential benefits of these technologies. These findings contrast with the conclusions of Sacks *et al.* (2020), who argue that the simultaneous combination of Lean Construction principles with DTs is an effective strategy for improving the outcomes implementations.

Respondents identified the Perceived Usefulness of DTs as a key factor. They agreed that DTs enhance efficiency (PU4) and improve decision-making (PU3). This fidings aligns with Bajpai and Misra (2023), who highlights stakeholders' perceived benefit of digitalization as the key drive. It also aligns with Aliu and Oke (2023), who identified improved operational structures as the main benefit of DTs. Additionally, it supports the improvement of analysis and decision-making assistance, as discussed by Altan and Işik (2024). These benefits are directly related to the ability to meet customer expectations, increasing efficiency, and enhancing decision-making. The perception of these benefits significantly influences Attitude Towards Technology Use, confirming H1b.

Respondents also considered Attitude Toward Technology Use an important factor, as it influenced their Intention to Use, confirming H1. This suggests that they are open and receptive to incorporating innovations into their professional practices. Such a favorable attitude is critical for driving the adoption of these technologies in the sector, as also observed in the surveys conducted by BIM Fórum Brasil (2022a, 2022b). It is essential that professionals recognize the benefits of a given DT, maintain a favorable Attitude Toward its use, and, consequently, develop the Intention to Use it, thereby contributing to its successful implementation.

Regarding the Organizational Aspects construct, it was observed that senior management is not fully engaged in the implementation of DTs. The lack of strong and committed leadership may hinder the development and execution of strategic planning for DTs, corroborating Aghimien *et al.* (2022). In line with this, respondents highlighted that companies often lack a strategic plan for DT implementation, a key factor identified by Dolla, Jain, and Kumar Delhi (2023) and Oke, Aliu, and Onajite (2024). Nevertheless, respondents generally agreed that an organizational culture supporting DT adoption exists within companies, suggesting an initial effort to integrate these technologies into companies' activities. In summary, improvements are needed in how companies approach the implementation of DTs.

Organizational Aspects positively influence the Intention to Use DTs, confirming H3. Thus, organizations must provide employees with the necessary conditions to effectively apply these technologies and reap the benefits they offer. Employees who work in an environment that fosters digital skill development, while feeling supported and encouraged, significantly contribute to the successful implementation and adoption of DTs.

With respect to the construct Necessary Resources, professionals demonstrated a strong understanding of the importance of assessing the costs associated with DTs before implementation, reflecting a cautious and strategic approach to investing in technological innovation. This indicates their awareness of the expenses related to acquiring and maintaining DTs, suggesting concerns about the return on investment, which aligns with the findings of Chen *et al.* (2024). Furthermore, the study highlighted the importance of having a robust technological infrastructure, including reliable hardware, up-to-date software, and a stable communication network. This finding is consistent with Zhang *et al.* (2023), who identified weak infrastructure as a barrier to digital transformation. Additionally, professionals expressed concern over data protection in a digital environment, recognizing that information security is crucial for the success and integrity of their projects and businesses, as noted also by Chen *et al.* (2024).

The importance of a qualified workforce was emphasized, reflecting the complexity of DT usage, as these technologies require specific technical knowledge to ensure effective application, as well as the quality and accuracy of results. This finding aligns with Oke *et al.* (2024a), who identified education and training as the most critical success factors for the adoption of DTs. Additionally, Oke, Aliu, and Onajite (2024) highlighted the shortage of qualified professionals and specialized knowledge as significant barriers, while Aghimien *et al.* (2022) emphasized the importance of workforce requalification to address these challenges. However, the way these items were formulated in the scale did not allow for assessing the perceived degree of difficulty regarding each resource. Contrary to hypotheses H5 and H6, which anticipated a negative relationship, this construct positively influences both Intention to Use and Current Capacity. It is argued that the more professionals recognize the importance of these resources, the greater their Intention and Current Capacity to use digital technologies. Therefore, this construct plays a crucial role in assessing the propensity to adopt DTs.

With respect to the Intention to Use construct, after considering the influences of Attitude Towards Use, Organizational Aspects, and Necessary Resources, it was found to have a positive influence on DT adoption, confirming H8. This result contrasts with studies from other developing countries, such as Oke, Aliu, and Onajite (2024), who identified a conservative mindset among professionals in the Nigerian construction industry, hindering DT implementation. These findings suggest that professionals in the Brazilian construction industry are open to the paradigm shift, demonstrating a greater willingness to adopt DT.

The construct Current Capability revealed a low perception of professionals that actively use DTs in their field, reinforcing this study’s findings on the slow adoption of DTs in Brazil, as observed in this research. In this context, Current Capability positively influences the Current Use of DTs, confirming H7.

The construct Current Use indicates that, although professionals are integrating digital tools into their daily practices, this integration remains in its early stages. In other words, while respondents may be familiar with certain tools, their use remains limited, lacking advanced applications and full integration across the organization and construction process. These findings highlight the need for a more comprehensive integration of digital tools across departments and throughout the construction project lifecycle.

Finally, the exploratory and confirmatory factor analysis led to the reorganization of various dimensions into more structured and manageable constructs, forming the final respecified model. These constructs, derived from participants' data, are significant as they represent the formal structure of the factors determining the propensity to use DT in the construction sector.

Conclusion

This study analyzes the factors influencing the propensity to use digital technologies (DT) in the Brazilian construction industry. Based on a survey of 144 professionals, the study first explores which digital technologies are used and the projects phases in which they are applied. Additionally, it provided a structural model explaining the determinants of the propensity to use these technologies.

Key findings indicate that BIM, Cloud Computing, Unmanned Aerial Vehicles, and Virtual Reality are the most widely adopted technologies. These findings, supported by previous literature, suggest progressive adoption of DTs in the Brazilian construction sector. Specifically, these technologies are increasingly used in the Design/Feasibility, Construction Management, and Execution phases, revealing that the primary goal is to improve construction efficiency. Thus, it can be concluded that digital transformation in the Brazilian construction sector remains slow and fragmented, requiring further advancements in the use and integration of these digital technologies along the construction project lifecycle.

The theoretical model developed and tested provides valuable insights into the factors that determine the propensity to use DTs. The findings confirm that Perceived Usefulness, Organizational Aspects, and Necessary Resources positively influence the Intention to Use DTs. Moreover, Necessary Resources positively affect Current Capacity and, together with the Intention to Use, influence the Current Use of DTs.

However, Ease of Use, Business Environment, and Lean Construction did not significantly influence the adoption of DTs. This suggests an opportunity for technological development in the sector, particularly through the application of technologies tailored to its specific needs in the sector. Furthermore, it underscores the need for government incentives, standardization, and data security to foster an environment conducive to innovation adoption and, consequently, to the digital transformation of the Brazilian construction sector.

Thus, this study contributes by offering a comprehensive overview of the current use of DTs in Brazil. Additionally, it provides insights into DTs adoption in Brazil's construction industry, introducing a model that can assist policymakers and managers in fostering digital transformation, particularly in developing countries.

Finally, despite the contributions of the research, the study has some limitations, which present opportunities for future studies. First, there is a potential bias resulting from self-administered questionnaires. Therefore, future research could further explore the use of DTs in the construction industry and the underlying factors presented in the structural model through more immersive research approaches, such as case studies.

Second, the study is geographically restricted to Brazil, and more specifically to the state of Ceará, which may limit the generalizability of the findings and requires parsimony when interpreting them in other contexts. Therefore, future studies could increase the sample by including other regions of Brazil to improve the robustness of the findings. Moreover, it would be interesting to compare different developing countries, or even developed and developing countries, as the factors are contextual and specific. Furthermore, larger sample sizes are both timely and desirable for testing and validating the proposed factor structure.

Third, the level of maturity was not assessed, which would significantly enhance the results. For instance, how are the most used technologies, such as BIM, Cloud Computing, Unmanned Aerial Vehicles, and Virtual Reality, being applied? What are the benefits of their application? Additionally, developing a maturity measurement model could be an important step toward addressing these questions.

Fourth and finally, the results for Lean Construction were unexpected, considering the positive relations suggested by previous literature. Therefore, exploration of this relationship in greater depth is recommended. Future studies could compare the level of DT use in Lean companies with their counterparts. Additionally, a theoretical model should be developed, incorporating more fine-grained aspects of Lean Construction, beyond the limited aspects explored in this study.

References

AGHIMIEN, D. *et al.* Delineating the people-related features required for construction digitalisation. **Construction Innovation**, v. 24, n. 7, 2022.

AJZEN, I. The theory of planned behavior. **Organizational Behavior and Human Decision Process**, v. 50, p. 179–211, 1991.

ALIU, J.; OKE, A. E. Construction in the digital age: exploring the benefits of digital technologies. **Built Environment Project and Asset Management**, v. 13, n. 3, p. 412–429, 2023.

ALMATARI, H. A. Q.; CHAN, M.; MASROM, M. A. N. Factors inhibiting the adoption of industrial revolution 4.0 in Malaysian construction industry. **Smart and Sustainable Built Environment**, v. 13, n. 4, p. 1041–1065, 2024.

ALTAN, E.; IŞIK, Z. Digital twins in lean construction: a neutrosophic AHP – BOCR analysis approach. **Engineering, Construction and Architectural Management**, v. 31, n. 12, p. 5029–5056, 2024.

BAJPAI, A.; MISRA, S. C. A framework for continuation of digitalization in construction: a PLS-SEM approach. **Engineering, Construction and Architectural Management**, v. 30, n. 10, p. 4715–4734, 2023.

BIM FÓRUM BRASIL. **Primeira pesquisa nacional sobre digitalização das engenharias na indústria da construção**. São Paulo: BIM Fórum Brasil, 2022a.

BIM FÓRUM BRASIL. **Primeira pesquisa nacional sobre digitalização na arquitetura e urbanismo:** conhecer para modernizar. São Paulo: BIM Fórum Brasil, 2022b.

CHEN, X. *et al.* A multivariate regression analysis of barriers to digital technologies adoption in the construction industry. **Engineering, Construction and Architectural Management**, v. 31, n. 11, p. 4281–4307, 2024.

CHEN, X. *et al.* Implementation of technologies in the construction industry: a systematic review. **Engineering, Construction and Architectural Management**, v. 29, n. 8, p. 3181–3209, 2022.

COSTA, F. J. DA. **Mensuração e desenvolvimento de escalas:** aplicações em Administração. Rio de Janeiro: Ciência Moderna, 2011.

DAVIS, F. D. Perceived usefulness, perceived ease of use, and user acceptance of information technology. **MIS Quarterly,** v. 13, n. 3, p. 319–340, 1989.

DOLLA, T.; JAIN, K.; KUMAR DELHI, V. S. Strategies for digital transformation in construction projects: stakeholders' perceptions and actor dynamics for Industry 4.0. **Journal of Information Technology in Construction**, v. 28, p. 151–175, 2023.

ELGHAISH, F. *et al.* Toward digitalization in the construction industry with immersive and drones technologies: a critical literature review. **Smart and Sustainable Built Environment**, v. 10, n. 3, p. 345–363, 2021.

ERNSTSEN, S. N. *et al.* How innovation champions frame the future: three visions for digital transformation of construction. **Journal of Construction Engineering and Management**, v. 147, n. 1, 2021.

FÁVERO, L. P. *et al*. **Análise de dados:** modelagem multivariada para tomada de decisões. Rio de Janeiro: Elsevier, 2009.

FERNANDES, L. L. de A.; COSTA, D. B. A conceptual model for measuring the maturity of an Intelligent Construction Environment. **Architectural Engineering and Design Management**, v. 20, n.6, p.1403–1426, 2024.

FISHBEIN, M.; AJZEN, I. **Predicting and changing behavior:** the reasoned action approach. Hove: Psychology Press, 2015.

HAIR, J. F. *et al.* **Análise multivariada de dados**. 6. ed. Porto Alegre: Bookman, 2009.

HOFMAN, B.; VRIES, G. de; KAA, G. Keeping things as they are: how status quo biases and traditions along with a lack of information transparency in the building industry slow down the adoption of innovative sustainable technologies. **Sustainability**, v. 14, n. 13, 2022.

HWANG, B.-G.; NGO, J.; TEO, J. Z. K. Challenges and strategies for the adoption of smart technologies in the construction industry: the case of Singapore. **Journal of Management in Engineering**, v. 38, n. 1, 2022.

MCDONALD, R. P. **Test theory:** a unified treatment. New York: Routledge, 2011.

NGUYEN, T. *et al.* Interrelationships among enabling factors for BIM adoption in construction enterprises. **Engineering Construction and Architectural Management**, v. 31, n. 2, p. 891–918, 2024.

OKE, A. E *et al.* Robotics and automation for sustainable construction: microscoping the barriers to implementation. **Smart and Sustainable Built Environment**, v. 13, n. 3, p. 625–643, 2024c.

OKE, A. E. *et al.* Success factors of digital technologies (DT) tools adoption for sustainable construction in a developing economy. **Construction Innovation**, v. 24, n. 4, p. 950–964, 2024a.

OKE, A. E. *et al*. Adoption of cloud computing tools for sustainable construction: a structural equation modelling approach. **Journal of Facilities Management**, v. 21, n. 3, pp. 334-351, 2023.

OKE, A. E.; ALIU, J.; ONAJITE, S. A. Barriers to the adoption of digital technologies for sustainable construction in a developing economy. **Architectural Engineering and Design Management**, v. 20, n. 3, p. 431–447, 2024.

OKE, A. E. *et al.* Appraisal of awareness and usage of digital technologies for sustainable wellbeing among construction workers in a developing economy. **International Journal of Construction Management**, v. 24, n. 5, p. 521–529, 2024b.

OLANREWAJU, O. I. *et al.* Modelling the relationship between Building Information Modelling (BIM) implementation barriers, usage and awareness on building project lifecycle. **Building and Environment**, v. 207, 2022.

SACKS, R. *et al.* Construction with digital twin information systems. **Data-Centric Engineering**, v. 1, 2020.

SACKS, R. *et al*. **BIM handbook:** a guide to building information modeling for owners, managers, designers, engineers and contractors. 3. ed. New York: Wiley, 2018.

SHAWHNEY, A.; RILEY, M.; IRIZARRY, J. **Construction 4.0:** an innovation platform for the built environment. Abingdon: Routledge, 2020.

SIJTSMA, K.; PFADT, J. M. Part II: on the use, the misuse, and the very limited usefulness of cronbach's alpha: discussing lower bounds and correlated errors. **Psychometrika**, v. 86, n. 4, p. 843–860, 2021.

TANAKA, C. A.; MATSUDA, P. M.; MACLENNAN, M. L. F. Transformação dital a construção civil no Brasil: estratégias adotadas de desenvolvimento. **Gestão & Regionalidade**, v. 40, n. 2024, p. e20248242, 2024.

TAYLOR, S.; TODD, P. Assessing IT usage: the role of prior experience. **MIS Quarterly: Management Information Systems**, v. 19, n. 4, p. 561–568, 1995.

VERINA, N.; TITKO, J. Digital transformation: conceptual framework. In: INTERNATIONAL SCIENTIFIC CONFERENCE CONTEMPORARY ISSUES IN BUSINESS, MANAGEMENT AND ECONOMICS ENGINEERING, 6., Vilnius, 2019. **Proceedings […]** Vilnius: Vilnius Gediminas Technical University, 2019.

WANG, K. *et al.* From Industry 4.0 to Construction 4.0: barriers to the digital transformation of engineering and construction sectors. **Engineering, Construction and Architectural Management**, v. 31, n. 1, p. 136–158, 2024.

WESTERMAN, G. *et al.* **Digital transformation:** a roadmap for billion-dollar organizations. MIT Center for digital business and capgemini consulting, 2011.

WONG, C. F. *et al.* Critical factors influencing the adoption of building information modelling (BIM) using technological adoption framework and structural equation modelling. **Engineering, Construction and Architectural Management**, v. 32, n. 2, p. 967–986, 2025.

ZHANG, N. *et al.* Digital transformation in the chinese construction industry: status, barriers, and impact. **buildings**, v. 13, n. 4, 2023.

Larissa de Moraes Rocha
Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing.

Departamento de Engenharia Estrutural e Construção Civil | Universidade Federal do Ceará | Av. Mister Hull, s/n, Bloco 733, Pici | Fortaleza – CE – Brasil | CEP 60455-760 | E-mail: larissamoraesrocha@yahoo.com.br

Luis Felipe Cândido
Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing.

Universidade Federal do Ceará | Av. Prfa. Machadinha Lima, s/n, Campus de Crateús | Crateús – CE – Brasil | CEP 63700-000 | E-mail: luisfcandido2015@gmail.com

José de paula Barros Neto
Conceptualization, Supervision, Validation, Writing – review & editing.

Departamento de Engenharia Estrutural e Construção Civil | Universidade Federal do Ceará | E-mail: jpbarros@ufc.br

Editor: **Enedir Ghisi**

Editora de seção: **Luciani Somensi Lorenzi**

Ambiente Construído
Revista da Associação Nacional de Tecnologia do Ambiente Construído
Av. Osvaldo Aranha, 99 - 3º andar, Centro
Porto Alegre – RS - Brasil
CEP 90035-190
Telefone: +55 (51) 3308-4084
www.seer.ufrgs.br/ambienteconstruido
www.scielo.br/ac
E-mail: ambienteconstruido@ufrgs.br