ARTIFICIAL INTELLIGENCE FEASIBILITY IN CONSTRUCTION INDUSTRY

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Abstract

Artificial Intelligence (AI) has a great impact on increasing productivity and economic growth in many sectors. However, in the construction industry, AI is still limited to research and few pilot projects. This study aims to depict the current rate of AI adoption in the industry and understand the obstacles that are hindering the required changes in the companies' business models. The data are collected through a tailored questionnaire sent to experts and practitioners in the field. The results show that labour-skilled shortage, data quality, cost-benefit and lack of case studies and standards have been identified as major issues. The findings help to understand the needs of construction practitioners and propose possible solutions.

Introduction

The Architecture, Engineering & Construction (AEC) industry is a key sector in the European Union (EU) since it accounts for up to 9% of the GDP and provides more than 6% of European employment (Baldini et al. 2019). Nonetheless, compared to other sectors, the productivity level reached by the industry is dramatically low, where many construction projects suffer from overruns in cost and time. This delay might be caused by the low digitalisation of the sector: according to the McKinsey Global Institute (MGI) Industry Digitization Index, construction is in the last position in Europe and second to last in the United States (McKinsey Global Institute 2017). On top of that, the current labour shortages, the COVID-19 epidemic, and the need to build sustainable infrastructures have accelerated the need for rapid change toward greater digitisation.

Recently, inspired by the "Industry 4.0," Artificial Intelligence (AI) applications have gained momentum and possess all the features to serve as the backbone to promote proper digital strategies in AEC (Darko et al. 2020, Pan & Zhang 2021). According to MGI (Chui et al. 2018), the potential value of AI for the global economy is $13 trillion by 2030, equating to a 16 per cent increase in cumulative GDP compared to 2018. Albeit there are multiple definitions of AI, the High-Level Expert Group (HLEG), appointed by the EU commission, defines AI as "software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal." (Annoni et al. 2018). (Pan & Zhang 2021) identified the benefits provided by AI in AEC, here summarized:

- Automation: AI makes project management more technically automatable and objective. AI-based solutions help overcome specific shortcomings of traditional construction management, which relies on manual observation and operation, therefore more prone to bias and confusion.
- Risk mitigation: Even in significant uncertainty, AI can monitor, detect, evaluate, and anticipate possible risks in terms of safety, quality, efficiency, and cost across teams and work areas.
- High efficiency: AI approaches are significantly used in optimisation challenges to make the building project operate more smoothly and efficiently.
- Digitalization: BIM has taken the lead in digitalizing the construction sector, going well beyond 3D modeling to give a pool of information about the whole project lifecycle. BIM can interact with AI to simplify the digitization of information in intelligent AEC processes.

Although these advantages have piqued the interest in the AEC sector, most of the studies come from Research and Development (R&D) projects. The industry's current diffusion of AI applications has not yet been investigated. However, a flourishing ecosystem of start-up enterprises is presently known as "Construction Tech", which has expanded from $250 million in 2013 to $1,000 million in 2018 (Sacks et al. 2020). Therefore, this study is an exploratory analysis of the current AI adoption in the construction industry to highlight deployment margins and future strategic plans for greater penetration of digital technologies.

Finally, the recent literature is mainly concerned with researching AI applications, potentials, advantages, and trends (Darko et al. 2020, Pan & Zhang 2021, Sacks et al. 2020). There is, however, a gap in evaluating the barriers or the incentives recognised by building specialists. These factors are critical for the long-term use of AI in the construction industry. For this reason, this study surveys the construction community to identify the main challenges and obstacles that, if surpassed, can drive the changes needed for disseminating AI into AEC processes.

Methodology

This section depicts the research topics and the method used to gather and analyse data.

Research methods

The following research issues are addressed in this paper:

- What is the present AI usage in building practices?
- What are the perceived advantages of employing AI in building practices?
- What are the main obstacles and challenges associated with the use of AI in building practices?

In the survey, such questions were divided into several sub-questions that help to identify specific advantages and disadvantages of AI introduction in AEC.

Questionnaire survey

To reach the largest number of people in Europe, we employed an online questionnaire prepared on Microsoft Forms ®. The poll was conducted between September 3rd and October 30th, 2021, and different channels were used to reach out professionals and practitioners: first, many actors were reached via mail using industry organizations such as Associazione Nazionale Costruttori Edili (ANCE), a national association of construction companies in Italy. In this way it was possible to contact professionals relevant to our research, encouraging their participation through the prestige of the associations involved. Moreover, the questionnaire was also publicly disseminated through social media like Linkedin ®and Twitter ®.

The online survey divided into four sections (Table 1): the first collected information about the respondents and their companies (e.g., company's size, practitioner's experience, and so on). The second section is used to distinguish companies that deploy AI from those that do not currently use it. Depending on the answer in section 2, the companies responded to questions in Section 3 -if they do not use AI in their processes-, or section 4 -if they use AI.

Consequently, the answers in Section 3 helped gather information on AI obstacles, whereas results from section 4 helped collect information about AI advantages and techniques used in AEC. Forty-three people completed the questionnaire, answering multiple choice and Likert scale (1 to 5) questions.

Data analysis

Overall, 43 professionals and researchers answered the questionnaire. One-third of the responses came from medium and big companies (i.e., with more than 100 employees), and the remaining two-thirds came from small enterprises (i.e., with less than 100 employees). This distribution reflects well the construction sector panorama where subcontractors and small enterprises are the majority (especially in Italy, where the response rate was the highest).

Although all participants were aware of the main concept of AI, a small portion of them were currently utilizing it: according to the responses, 20.9 % of the participants were actively utilizing AI, whereas the remaining 79,1% were not using AI at all. Most participants had 1-5 years (37%) of experience in the industry, followed by people with 6-15 years (24%), more than 25 years (21%), and 16-25 years (18%). Moreover, the participants mainly work for consultancy companies (39%), construction companies (21%) and software companies (10%). Finally, The majority of the response comes from firms operating in Italy (72%), United Kingdom (18%), and United States (4%).

Table 1: Questions asked in the online survey

Section	Topic	Question type
1. Identification	Determine the profile of the respondent	Multiple choices
2. Use of AI	Identify if the company use AI or not	Multiple choices
3.1 Stakeholder related obstacles	Identify possible obstacles coming from stakeholder	Likert scale
3.2 Financially related obstacles	Identify possible obstacles coming from financial aspects	Likert scale
3.3 Employee related obstacles to the AI adoption:	Identify possible obstacles coming from insufficient or untrained workforce	Likert scale
3.4 External environment-related obstacles	Identify possible obstacles coming from environmental aspects such as lack of standards or guidelines	Likert scale
3.5 Software related obstacles	Identify possible obstacles coming from lack of AI software	Likert scale

Section	Topic	Question type
4.1 Rate the advantages that AI brings to your company	Identify main advantages in using AI for AEC processes	Likert scale
4.2 Rate the obstacles found towards AI adoption	Identify obstacles met in the AI adoption path	Likert scale
4.3 AI technology used	Identify most common AI technologies adopted in construction companies	Multiple choices
4.4 The origin of the data used for AI	Identify how companies collect and use data for AI projects	Multiple choices

Benefits for AI adoption in AEC

Various advantages have previously been mentioned in the literature (Pan & Zhang 2021, Bolpagni et al. 2021, Sacks et al. 2020), but most of these benefits came from the academic and research point of view. This section assessed if AI-practitioners in the construction industry also recognise the main benefits identified by the literature. Figure 1 shows the main advantages identified through the survey.

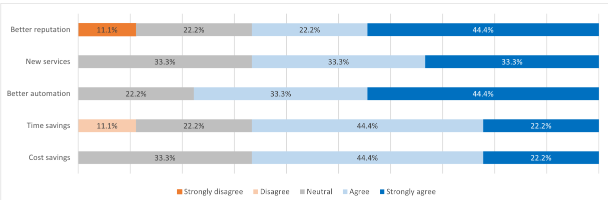

Figure 1: AI advantages found by the companies that use AI.

Automating AEC tasks (78%) results in the main advantage that helps overcome some of the drawbacks of traditional construction management, which is more prone to bias since it relies on manual observation and operation. In this context, Machine Learning (ML) algorithms, for example, are used to intelligently learn the mass of gathered data for hidden knowledge discovery, and they are also integrated into project management software to make automatic data analysis and decision making easier (Hu & Castro-Lacouture 2019). Moreover, most respondents agree that time (66%) and cost (66%) savings have been achieved thanks to AI technologies. This result resonated with the survey conducted by the MGI (McKinsey 2021), where respondents reported much higher cost savings from AI than they did previously. Finally, the implementation of AI would benefit the company's business by introducing new services (66%) and increasing the company's image and reputation (66%) (Figure 1).

Barriers for AI adoption in AEC

To date, a comprehensive and critical analysis of the issues that enterprises face when they try to implement AI in their processes is missing, but it is required to convey the right research questions:

(Bérubé et al. 2021) demonstrate that AI faces several unique challenges, including a lack of management awareness of AI's commercial and technical potential, due to the scarcity of skills for designing algorithms. The study also revealed how the nature of AI, particularly its reliance on data, presents implementation challenges such as data quality, data quantity, and data governance concerns. In the construction sector, (Bolpagni et al. 2021) researched the level of AI adoption in the industry. However, the study focused on determining the ethical aspects of AI, analyzing the risks perceived by construction practitioners rather than focusing on the obstacles that hinder AI widespread dissemination.

Consequently, this study is the first experimental work for detecting the main challenges that our industry is facing towards an higher adoption of AI in AEC. The survey differentiated the questions based on whether the company utilizes AI or not. In this way it was possible to compare the obstacles perceived by non-AI companies with those encountered by enterprises that are currently using AI. Figure 2 reports the main problems that prevented companies from using AI. According to the results, the two most important topics are the difficulty in finding and managing an adequate amount of data (62%) and AI-skilled employees (79%). Other concerns are the lack of case studies (58%) and standards (44%), which can offer a methodology or best practices to follow.

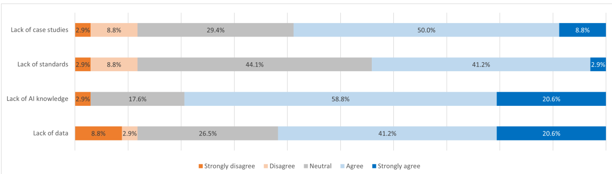

Figure 2: AI obstacles according to companies that do not use AI.

Despite the identified obstacles, many respondents are developing strategies to surpass these problems and aim to implement AI in the next 1-2 years (10%), in the next 2-5 years (24%) or the long term (3%).

Similar feedback was given by participants using AI (Figure 3), suggesting that awareness of key issues in the industry is shared. Most of them had difficulties in getting data (67%) and AI-skilled personnel (78 %), while costs (11%) and privacy (22%) did not represent a big issue. Finally, relevant concerns were encountered in adapting the hardware to the new technologies (55 %). In the following paragraph we will analyze these barriers in detail trying to propose possible solutions to overcome them.

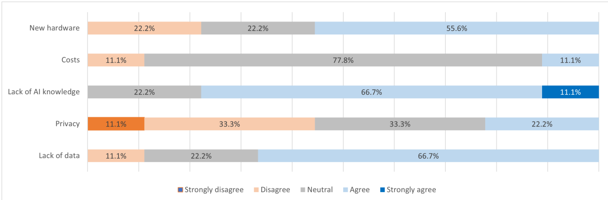

Figure 3: AI obstacles according to companies that use AI.

Challenges in deploying AI in AEC

The survey stressed multiple obstacles hindering the wider adoption of AI in AEC. In this section, we explored four challenges derived from the barriers: the shortage of AI-skilled workers, the data-quality challenge, the cost-benefit challenge and the lack of case studies or standards.

Shortage of AI-skilled workers

AI is projected to increasingly revolutionize economies, change the business environment, and play a critical role in assisting businesses in achieving their objectives and improving their key performance metrics. Therefore, according to Forbes (Swathi 2021), the demand for AI-trained personnel will rapidly increase in the coming years. Many industrialized economies throughout the world, most notably the European Union (EU) and the United States (US), have policies in place to promote the adoption of AI technology. The EU engages with business, researchers, and academia to develop the data value chain and promote the data-driven economy. For example, the Horizon Europe is the largest research and innovation project, with almost 95.5 billion euros in financing development of AI technologies (European Commission and Directorate-General for Research and Innovation 2014). Academic institutions have been increasing machine-learning and AI-related programs, but industry demand for machine-learning-educated workers will take years to satisfy. When the need for talented machine-learning engineers grows quickly, finding qualified candidates becomes difficult, and employee retraining becomes increasingly critical. Governments may provide their workforce with a competitive advantage by educating, developing, and enabling access to people with sophisticated computer and analytics skills. Because AI education necessitates hands-on experience, industry and academia should work together to develop apprenticeship programs that allow students to rotate around multiple firms and learn about AI applications in a variety of sectors and job functions (Johnson et al. 2021). Employers must be able to share their expertise with students through academia.

Data quality challenge

The suitability of data for the specific aim of machine-learning applications is referred to as data quality. High-quality data is a far more critical aspect than quantity for the effective application of ML to real-world situations, (Gordon 2021). Data quality is vital while training machine-learning systems, but it is much more important for assuring trust in the applications' choices. Data quality deteriorates when data becomes increasingly unstructured and gathered from more sources. While structured information is necessary for machine learning, more data is generated in unstructured formats (e.g., text, video, and picture data), which standard data-management tools cannot handle. Machine-learning programs will need to recognize and take unstructured input in real-time. To generate quality measurements, gather new data, evaluate data quality, eliminate wrong data from the training data set, and analyze the trade-off between quality-assurance costs and gains, companies should construct a data-quality assessment process. (Cichy & Rass 2019) identified 12 main data-quality assessment models where the majority of techniques use objective measures or a combination of analytics and subjective measurements. One of the main is the Total Data Quality Management (TDQM), whose steps are shown in 2. Specifically to AI applications, (Heo et al. 2021) identified three main steps that lead to efficient management of data:

- Data acquisition: Pictures or time series data were formerly copied into digital form. Due to copyrights and personal information protection, it is challenging to use existing data indiscriminately for R&D with commercialization aims or done in specific professional sectors. A mechanism to validate the data individually after the acquisition is required. Although there is a tool to automate this procedure, it cannot be considered full; consequently, human intervention is needed throughout all steps.
- Data Refinement/Labeling: it has been demonstrated that a refinement manager and developing personnel with academic knowledge of the development field were required to improve AI models accuracy.
  Moreover, data refined by personnel with professional development education rather than the general public is a critical component of a correct data-quality strategy.
- Data Quality Evaluation: managers should carry out quality evaluation for each step included in AI processes.

Cost-benefit challenge

In the construction industry, the advantages of AI-driven solutions are now well demonstrated in the literature. However, the early expenses of investing in AI technologies, such as robotics, are typically very high. Therefore, firms must identify areas of critical need and determine which AI-powered use cases will have the most effect in the short term. Construction businesses will be inefficient in their time and resources if they don't have a clear business case, ROI, or burning platform, leading to dissatisfaction, increased scepticism, and a loss of momentum. Leaders should prioritize their investments based on the

Table 2: *Improvement steps of the TDQM*

Process	**Steps**
Assess data definition and information architecture quality	1. Identify data definitions quality measures 2. Identify information group to assess 3. Identify the information stakeholders 4. Assess data definition technical quality 5. Assess information architecture and database design quality 6. Assess customer satisfaction with data definition quality
Assess information quality	1. Identify an information group for assessment 2. Establish information quality objectives and measures 3. Identify the information value and cost chain 4. Determine file or processes to assess

areas where AI can influence the firm's particular circumstances and where it will be the simplest to execute at the firm's present level of digital maturity. It is also important to think about how much maintenance these solutions require. This could be prohibitively expensive for most subcontractors and small businesses that make up the construction sector. As a result, organizations must assess the cost savings and return on investment of such technologies before deciding whether or not to invest. Furthermore, as these technologies become more widely acknowledged and used in construction, prices will likely fall, making them more accessible to smaller businesses.

Lack of case studies or standards

Every disruptive technology causes societal changes that often necessitate some regulation. The first challenge in determining the most appropriate regulatory framework for AI is predicting its impact on society. The second is to keep up with the rapid advancement of artificial intelligence. Other obstacles include AI's complexity, autonomy, self-learning capabilities, and pervasiveness across industries. These characteristics necessitate a policy-making qualified interdisciplinary capacity (to understand technologies better and predict impact) as well as flexibility (to envision frameworks that, while enforceable, can adapt over time). Regulatory sandboxes could be particularly useful in this regard.

Industry standards and structured data are also key components for better interoperability. This implies that information may be linked together by people and technology, allowing the extraction of more useful knowledge. Consistency, repeatability, and predictability are all achieved using the same information formats across industries. Businesses will see actual efficiency advantages due to this, and the data architecture for the connected future will be in place.

AI techniques in AEC

In the history of AI, there have been ups and downs with logic-based techniques in the 1950s and early 1960s, knowledge-based expert systems in the 1970s and 1980s, and data-driven approaches (from 2000 onwards), all with periods of disillusionment and reduced funding in between. Currently, we are entering a new era of high expectations, fueled by greatly enhanced computational processing power and data (Annoni et al. 2018).

Therefore, the questionnaire is a significant opportunity to understand which techniques are currently most popular in the industry. We asked the participants to use AI to highlight the current methods in their companies. The results are also compared with what has been published in the scientific literature to assess whether the most common techniques are the same. The research inside the literature has been done by querying the SCOPUS database with each of the techniques listed in Figure 4 combined with "building*" or "construction*" through the Boolean operator AND. In order to restrict the results only to articles relevant to the construction industry, we have limited the search to the journal ISSN listed (Scott et al. 2021). Figure 4 shows the comparison result: there is a strong correlation between the research focus in academia and the use of AI inside the industry. It is important to stress that Computer Vision and Natural Language Processing (NLP) are two applications of Deep Learning (DL), therefore articles retrieved from SCOPUS under the keyword DL may deal with those techniques, making the difference in Figure 4 smoother.

The most common technique that is leading this new wave of AI is ML: it refers to a system's ability to learn, decide, predict, adapt, and react to changes without being explicitly programmed. Specifically, with ML in this study, we refer to shallow models that do not include DL techniques, considered in a separate category. Many shallow learning techniques have been used to solve construction related problems (e.g., Linear Regression, Logistic Regression, Support Vector Machines (SVM), Decision Trees (DT), K-nearest Neighbors (KNN), and shallow neural networks) (Rampini & Re Cecconi 2021). ML approaches were mainly used in five common parts of construction project management, including risk assessment and reduction (Gondia et al. 2020), construction site safety management (Harirchian et al. 2020), cost estimation and prediction (Rafiei et al. 2018), schedule management (Son et al. 2012), and building energy demand prediction (Rahman et al. 2018). Moreover, reinforcement learning usually covers control strategies for thermal energy management in buildings (Brandi et al. 2022).

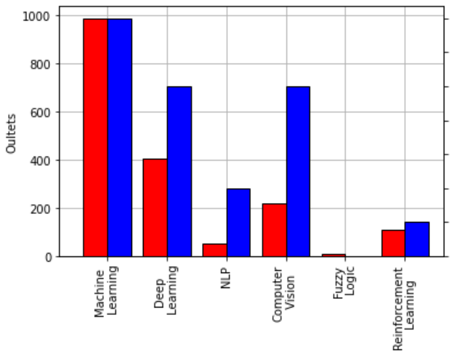

Figure 4: Distribution of AI techniques used in the construction industry. The red bar plots the amount of scientific articles related to a specific technique, while the blue bar indicates the responses given by AI-practitioners in the questionnaire.

DL is a subset of ML that is essentially a three or more layer neural network. These neural networks aim to imitate the activity of the human brain by allowing it to "learn" from enormous amounts of data, albeit they fall far short of its capabilities. While a single-layer neural network may produce approximate predictions, additional hidden layers can help to optimize and improve for accuracy. Currently, DL techniques are used for two tasks: Computer Vision, referred to actions that identify human faces and objects in digital photographs or videos; and NLP, considered as the machine's ability to recognize, analyze, comprehend, and/or generate data in written and spoken human communications. According to (Martinez et al. 2019) Computer Vision (CV) applications in construction covers four main topics: Construction safety and personnel monitoring (Seo et al. 2015), Resource tracking and activity monitoring (Yang et al. 2015), Surveying and as-is modeling (Ptrucean et al. 2015, Rampini et al. 2022), and Inspection and condition monitoring (Spencer et al. 2019). On the other hand, NLP techniques are mainly used for compliance checking (Zhang & El-Gohary 2017) and risk prediction (Li et al. 2021).

Conclusions

There is no denying that we are living in a digital age. Industry 4.0 is bringing digitization to processing and manufacturing organizations, allowing them to employ concepts like the Internet of Things and automation to boost efficiency and safety while reducing environmental impact. Nonetheless, in the construction sector AI's proliferation is currently modest.

However, thanks to the growing amount of data generated during the building lifecycle and the increased computing capacity of hardware, contractors, operators, owners, and service providers across the project lifecycle can no longer afford to think of AI as a niche technology. To foster the renovation process is crucial to understand the potential benefits and the challenges introduced by new technology. In the scientific literature, many studies explored the advantages and the positive outcomes of deploying AI, but few (if none) of them focused on the challenges that companies face.

This research addresses this gap by surveying 43 professionals from the industry. The questionnaire has pointed out four main challenges that must be tackled to ease a wider AI adoption: i) shortage of AI-skilled workers, requiring a joint effort between industry and academia to promote programs that can develop an adequate amount of AI-skilled talents; ii) data quality, requiring an objective assessment and active management of information by collecting, keeping, and using data securely, efficiently, and cost-effectively; iii) cost-benefit, requiring AEC companies investing in the necessary data collecting and processing technologies (e.g., advanced analytics) and clear target area of intervention rather than chasing the most recent cool technology; iv) lack of case studies or standards, which requires governments and regulators to improve their efforts in producing industry standards and guidelines that encourage companies initiative and interoperability. Regarding this last point, it is worth mentioning the new Digital Twin standard development BSI 260 under development with the Flex method. As technologies advance, lessons are learned, and practical experience is accumulated across domains and countries, the Flex method allows incremental revision of the standard. Because of the intricacy and cross-domain nature of AI for construction also presents an opportunity to realign with associated standards.

Limitations and future work

In this research, data was gathered from practitioners in the construction industry who have already utilized digital tools and recognised their successes on a national or worldwide level. However, the data collected cannot fully represent the panorama of AI applications in the entire sector. The answers were collected during a global pandemic, and it is important to note that businesses are sometimes compelled to develop new techniques to deal with new, unexpected issues (e.g., the inability to operate onsite or the necessity to minimize resources). Finally, data should be collected regularly to track the progression of the phenomenon given the dynamic nature of the challenges presented here.

Acknowledgments

The authors would like to thank Mauro Ferrarini and Gloria Domenighini for their valuable support in disseminating the questionnaire.

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