Artificial Intelligence in Construction Projects: An Explorative Study of Professionals’ Expectations

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ABSTRACT

Artificial intelligence (AI) is a fast-growing innovative technology that will have a huge impact on projects and project management practices in the forthcoming years. The purpose of this paper is to contribute to project management theory and practice in the construction industry by analyzing the expectations of project professionals. A mixed method based on an international survey and semi-structured interviews was applied. The results show that construction project practitioners are looking for AI solutions to support the quantitative processes mainly related to scope, schedule, cost, quality, and risk management. However, the human-related processes, such as communication and stakeholder management, are not expected to be directly enhanced by AI, although might benefit from it indirectly. The findings also demonstrate a difference between amplifying and accelerating countries, where somewhat surprisingly the latter are more ready to adopt AI in their projects.

Keywords: Artificial Intelligence, Construction, Digital Readiness, Project Management.

I. INTRODUCTION

The continuously rapid advancement in technology is changing almost every aspect of organizational and managerial activities. The fast-growing discipline of Artificial Intelligence (AI) gets more and more attention from practitioners (Gartner, 2020; McKinsey Analytics, 2019; Ransbotham et al., 2017) and academics (Iansiti & Lakhani, 2020; Raisch & Krakowski, 2020) in different fields of management, and is expected to disrupt the field of project management (PM) as well (Auth et al., 2019; Lahmann, 2019; Parsi, 2019; PMI, 2019; Q. Wang, 2019).

Projects in the construction industry had taken a predominant role from the inception of the PM field (Betts & Lansley, 1995). Even though new sectors and non-traditional industries also apply PM practices (Carden & Egan, 2008), the construction industry still constitutes a major part of the evolving PM body of knowledge (Carden & Egan, 2008; Crawford et al., 2006). As a well-established domain of professional PM, the construction industry can, therefore, be an interesting case to investigate how new technologies, such as AI, have the potential to improve and reshape the profession.

AI was initially introduced in the 1950's aiming to replicate human intelligence using computer programs. Although throughout the years the field of AI experienced major fluctuations, mainly due to a mismatch between the level of expectations and the level of available applications (Haenlein & Kaplan, 2019), it seems that current AI technologies are mature enough to provide substantial improvements in different aspects in the workplace, including project operational and managerial processes.

The aim of this paper is to analyse construction project practitioners’ expectations with regard to AI being applied to PM processes and practices. The paper starts with an introduction to AI. The next section reviews AI applications in the context of construction PM, by knowledge areas. Then, the research question and methodology are described, followed by reporting the research findings. The paper is finalized with a discussion of the main insights and concluding remarks on the limitations of the current study and directions for further research.

II. ARTIFICIAL INTELLIGENCE

The term “Artificial Intelligence” (AI) was introduced in the 1950’s with the seminal works of Alan Turing (Turing, 1950) and John McCarthy and colleagues (McCarthy et al., 2006), with reference to replicating human intelligence by using computer programs. Since then, and following developments of related technologies, the discipline of AI had experienced fluctuations in the level of interest by scholars and practitioners (Haenlein & Kaplan, 2019), which is also demonstrated in the various definitions that were suggested. Some definitions focused on rational reasoning and acting, as Charniak and McDermott (1985) defined AI as “the study of mental faculties through the use of computational models”, and Winston (1993) defined AI as “The study of the computations that make it possible to perceive, reason, and act”. Other definitions emphasized the behavioral and human performance. For example, Kurzweil (1990) defined AI as “The art of creating machines that perform functions that
require intelligence when performed by people”, while Rich and Knight (1991) defined AI as “The study of how to make computers do things at which, as the moment, people do better”, and Luger (2005) defined AI as “the branch of computer science that is concerned with the automation of intelligent behaviour”. Recent approaches to AI take into consideration the external environment and the relevant goals to be achieved, thus defining AI as “systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals” (EC, 2018), or as “a system’s ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation” (Kaplan & Haenlein, 2019).

The current paper adopts the recent approaches, therefore suggesting that AI is based on the increasing capabilities of technology to analyse data, learn, perform tasks that are currently performed by humans, and adaptively interpret external conditions. In the context of project management, it means that AI technologies can be used to autonomously perform routine tasks and to support the project manager’s work by recommending preferred decisions and actions based on the machine’s competence to be adaptive to different environments and situations.

AI technologies are classified based on levels of specialization and intelligence. Narrow AI (NAI) refers to applications that are focused on a single subset of cognitive abilities to learn and do well only what they were designed for, within a specific spectrum, therefore usually used to automate specific tasks and improve efficiency. Examples in the context of project management might include optimal resource allocation, optimal project schedule, or optimal contract prices for the procurement of goods. General AI (GAI) includes intelligent applications that can autonomously learn and perform as, or even better than, humans on a wide range of tasks (Borana, 2016; Deloitte, 2018). GAI for project management might be in the form of project portfolio selection, analysing customer requirements, or optimizing operation and site safety. The highest level of AI, named Super AI or superintelligence, refers to systems that exceed human intelligence and abilities (Boström & Yudkowsky, 2014; Müller & Boström, 2016), defined by Boström as “intelligents that greatly outperform the best current human minds across many very general cognitive domains” (Boström, 2014, p. 52). However, there is no consensus on if and when it will be possible to develop superintelligence systems, (see Alfonseca et al., 2021; Jebari & Lundborg, 2020), and there is a wide agreement that the current state of the art in AI cannot support superintelligence.

### III. AI IN CONSTRUCTION PM KNOWLEDGE AREAS

A review of recent literature on AI applications for improved management of construction projects, based on the 10 knowledge areas defined by the PMI (2017), can be summarized into two major categories: processes for which AI applications have already been proposed, and processes that were not addressed in the literature, yet.

| TABLE I: REVIEW OF AI APPLICATIONS FOR PROCESSES IN CONSTRUCTION PROJECTS |
| --- |
| **Existing AI applications** | **Missing AI applications** |
| Integration | Manage Project Knowledge | Develop Project Charter |
| | | Develop Project Management Plan |
| | | Direct & Manage Project Work |
| | | Monitor & Control Project Work |
| | | Perform Integrated Change Control |
| | | Close Project/Phase |
| Scope | Collect Requirements | Define Scope |
| | Create WBS | Control Scope |
| | Validate Scope | |
| | Sequence Activities’ | |
| | Estimate Activity | |
| Schedule | Durations | Plan Schedule |
| | Develop Schedule | Management |
| | Control Schedule | Define Activities |
| Cost | Estimate Costs | Plan Cost Management |
| | Control Costs | Determine Budget |
| Quality | Control Quality | Plan Quality Management |
| Resource | Estimate Activity Resources | Manage Quality Plan Resource Management |
| | Develop Team | Acquire Resources |
| | Manage Team | Control Resources |
| Communication | Manage Communications | Plan Communications Management |
| | Identify Risks | Monitor Communications |
| | Perform Qualitative Risk Analysis | |
| | Risk | Perform Quantitative Risk Analysis | Plan Risk Management |
| | | Plan Risk Management Implement Risk Responses |
| | | Monitor Risks |
| Procurement | Conduct Procurements | Plan Procurement Management |
| | Control Procurements | Identify Stakeholder Plan Stakeholder Engagement |
| Stakeholder | Manage Stakeholder Engagement | Monitor Stakeholder Engagement |

* Studies are not specific to construction projects. However, due to their general features, they could be applied to construction projects.

The following sections present a brief overview of each one of the knowledge areas.

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**A. Project Integration Management**

Project integration management provides the foundation for the other interdependent knowledge areas to initiate, plan, execute, control, and close a project in a consistent and coordinated manner (PMI, 2017). Although current literature does not refer to AI for project integration management, the process of managing project knowledge can be addressed by Building Information Modeling (BIM), which consists of 3-D digital representations and involves tools of graphical design and information storage and management (Yalcinkaya & Arditi, 2013). AI technologies such as machine learning (ML) and artificial neural networks (ANN) have the potential to manage explicit and tacit knowledge in construction projects to encode visual building information (Ho et al., 2013; Sacks et al., 2020; Singer et al., 2016).

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**B. Project Scope Management**

Project scope management groups all the processes required to outline the essential work needed to successfully
achieve the project objectives. The tools and techniques used to plan scope management are complex to automate and highly influenced by the context. However, to collect requirements Zhang and El-Gohary (2016) propose a semantic rule-based Natural Language Processing (NLP) algorithm and for requirements traceability, Di Thommazo et al. (2014) suggest AI technology to detect the level of dependency between different requirements. To Create work breakdown structure (WBS), Siami-Irdemoosa et al. (2015) propose the use of hierarchical ANNs for underground construction based on the WBS levels to provide higher quality solutions by learning over time. Finally, to validate the scope, computer vision was proposed by Ibrahim et al. (2009) to support real-time inspection and assessment of the progress made on a construction site, using virtual cameras.

C. Project Schedule Management

Project schedule management deals with the processes that enable “the timely completion of the project” (PMI, 2017, p. 173). To estimate activity durations Wauters and Vanhoucke (2016, 2017) offer to use Support Vector Machine (SVM) for effective and more accurate forecast estimations, even at the early stages of a project. For sequence activities, ANNs are used to define the logical relationship between two or more activities, as Golpayegani and Parvaresh (2011) propose. In order to develop schedule, Genetic Algorithm (GA) can be used to retrieve information and optimize multiple variables simultaneously for the purpose of producing an accurate project schedule, identifying the critical path and effectively level resources (Agarwal et al., 2011; Aziz et al., 2014; Faghhi et al., 2014; Li et al., 2018). For the process of control schedule, Chao and Chien (2010) propose a model combining ANNs preliminary estimates and progress-matching subsequent estimates to update the S-curve, which shows the relationship between time and project progress, of a construction project by gradually changing the relative weights for forecasting.

D. Project Cost Management

Project cost management includes all the processes related to the economic and financial aspects of a project. The process of cost estimate has been widely investigated to generate, at the early stages of a project, reliable and accurate approximations of the required monetary resources. Various studies report on the effective use of AI techniques such as ANNs, GA, Fuzzy Logic (FL), and SVM for this purpose (Arata & Alqaedra, 2011; Cheng, Tsai, et al., 2010; Cheng & Roy, 2011; Rafiei & Adeli, 2018). AI can be also useful for related topics such as vendor bid analysis (Chou et al., 2015) or contingency reserve (Lhee et al., 2014). As for the control costs process, AI offers solutions to forecast earned value indexes (Aidam et al., 2020) and to better estimate the project completion cost (Cheng et al., 2012; Cheng, Peng, et al., 2010; Wauters & Vanhoucke, 2017).

E. Project Quality Management

Project quality management processes define standards and assessment procedures to plan, manage and control the project and product quality requirements, with the aim to meet stakeholders’ objectives and continuously improve (PMI, 2017). Literature on the use of AI to manage quality in construction projects is rare, but insights can be taken from non-project activities, such as maintenance, as proposed by Liu et al. (2017) to check the quality of buildings’ facades using ML along with street view images. Although control quality in construction projects automated technologies had been used, this process is usually not based on intelligent technologies (Akinci et al., 2006). It does, however, imply that AI can be successfully implemented, for example by SVM to accurately detect construction materials using digital images (Rashidi et al., 2016).

F. Project Resource Management

Project resource management processes include identification, acquisition, and management of resources. To estimate activity resources, Chen et al. (2012) present an intelligent scheduling system, which exploits GA evolutionary techniques to estimate the near-optimum distribution of different construction resources, according to the project objectives and constraints. Following the same reasoning, García de Soto and Adey (2016) present how a combination of AI techniques can be jointly employed to accurately estimate the amount of concrete, reinforcement, and structural steel needed in a construction project. Previous studies on AI also addressed the process of developing a team, in terms of improving competencies and interactions to enhance the project performance (Munir, 2019; Strnad & Guid, 2010). To manage the team, i.e., to track team members’ performance, give feedback and take actions when needed, the AI bot used by Webber et al. (2019) improved team effectiveness, though it was examined only in a business school and not in a real work environment.

G. Project Communications Management

Project communication management relates to the processes of internal and external exchange of information throughout the project’s lifetime and is identified as one of the critical success factors in projects (Coughlan & Macredie, 2002; Hyväri, 2006). To manage communications AI could facilitate the retrieval of information from past construction project management documents to improve project knowledge management and support decision making in an easier and faster way (Ayodele & Kajimo-Shakanatu, 2021; Martínez-Rojas et al., 2016; H. Wang & Meng, 2019) and AI-based chatbot system that uses NLP can be used to automatically provide daily reports on construction projects (Cho & Lee, 2019). In this context, instant messaging applications and social media tools can be leveraged for effective communications in construction projects (Amade, 2017; Pozín et al., 2019; Remídez & Jones, 2012).

H. Project Risk Management

The processes in project risk management are aimed to identify and analyse the uncertain occurrences that can impact the project and determine which response strategies should be pursued. To identify risks, Bayesian Belief Network (BBN) is suggested, also in combination with FL, as an effective technique to capture risks and the relationships among them (Islam & Nepal, 2016; Khodakarami & Abdi, 2014; Qazi et al., 2016; Sousa & Einstein, 2012). For the following processes, i.e., perform qualitative/quantitative risk analysis, Odeyinka et al. (2013) suggest a reliable estimation model to predict the impact on the cost flow and Yazdani-Chamzini (2014) refer to the use of FL to reliably analyse the potential
risks in tunneling construction projects based on linguistic terms. To plan risk responses, optimal risk mitigation strategies for construction projects are assessed to select the ones that minimize risks (Qazi et al., 2016; Sousa & Einstein, 2012), while using AI techniques to consider resource allocation for critical events (Cárdenas et al., 2014) or to assess the effect that different actions have on other risks (Fang et al., 2013).

I. Project Procurement Management

Project procurement management includes the processes necessary to manage and control the acquisition of products and services from external sources. To conduct procurement, which deals with the search and selection of a seller to award a contract, intelligent mechanisms that are mainly based on FL can be used to produce a reliable and fast solution to assess subcontractors in construction projects (Lewis et al., 2011; Ulubeyli et al., 2017; Ulubeyli & Kazaz, 2016), while other AI techniques, such as GA, can be used to identify the optimal subcontractors for a specific work (Polat et al., 2015) or to forecast contractor’s deviation from a client’s objectives (Attar et al., 2013). To control procurement, Cheng et al. (2011) present a model that considers multiple factors by exploiting three AI techniques to provide a reliable performance evaluation, and Keshavarz-Ghorabaee et al. (2018), present a fuzzy dynamic multi-criteria group decision-making approach with the aim to assess subcontractors’ performance overtime.

J. Project Stakeholder Management

The processes in project stakeholder management include identification of all the people and organizations that could impact or be impacted by the project, analysing expectations, and developing appropriate management strategies. Thus, managing stakeholders’ processes involve high human-intensive activities.

The process of managing stakeholder engagement which consists in communicating and working with stakeholders in order to meet their expectations and solve any emerging issue was addressed in several publications. For example, Lv and El-Gohary (2016) suggest supervised ML algorithms technique analyse texts for the purpose of identifying types of concerns in the early project stage. Hester (2015) discusses the use of FL to map stakeholders’ behaviours and relationships over time, allowing “what-if” analyses for potential solutions to the expectations of stakeholders in a real estate developer’s project to turn a single-family home area into a condominium neighbourhood. And Sperry and Jetter (2019) present a similar approach where fuzzy cognitive maps are used to leverage stakeholders’ public comments to assess the project’s impact and manage conflicts due to various interests.

K. Summary

A literature review on AI in construction PM shows that despite recent advancements in technology, only limited solutions for improved practices are offered. Most solutions are used for estimations and predictions, in knowledge areas that are based on quantitative approaches such as cost, schedule, resources, procurement, and risk management. The ‘soft’ practices, such as communications, stakeholder, and integration management, are yet to be developed to benefit from future AI developments. There is an uncertainty with regard to the ways in which AI will impact the PM discipline in general (Auth et al., 2019; Holzmann et al., 2022; Munir, 2019; Parsi, 2019; PMI, 2019), and there is no agreement on the future of AI in the construction industry in particular (Pan & Zhang, 2021; Turner et al., 2021).

IV. RESEARCH AIM AND METHODOLOGY

The current study aims to explore the attitudes and expectations of construction project management practitioners in different countries. Specifically, the research questions are: (a) What are the perceived potential contributions of AI in each PM knowledge area? (b) What is the perceived impact on project success that will be derived from applying AI? and (c) What is the level of readiness to adopt AI solutions in construction projects?

Data was collected using a mixed methods approach through a survey and semi-structured interviews, which is a valid approach for exploratory studies (Creswell et al., 2003; Ivanikova et al., 2006; Williams, 2007). The survey provided answers related to “what are the expectations of project professionals with regard to AI technologies”, and the following semi-structured interviews provided an in-depth understanding of “why and how to integrate AI technologies in construction projects”. The combination of quantitative and qualitative methods strengthened the validity of the study, as previous studies on project management reports (e.g., Aarseth et al., 2014; Banihshemi et al., 2017; Shen et al., 2017; Ulubeyli et al., 2017).

A. Research Survey

A survey was used to obtain specific data from an array of practitioners working in construction companies in different countries. The survey contains two sections that were presented following an introduction to the study that explained the purpose of the survey. Section A includes statements about expectations, using a five-points Likert Scale of agreement (Strongly Disagree = 1, Strongly Agree = 5), which allows respondents to choose a neutral answer whenever they neither agree nor disagree, and in most cases can be interpreted as not having a clear opinion about the given statement (Chyung et al., 2017; Dawes, 2008). Following previous studies on expectations for AI (Fridgeirsson et al., 2021; Ransbotham et al., 2017), three recurring statements were presented for each of the ten knowledge areas: (1) I expect AI will significantly contribute to [knowledge area] in the next 10 years; (2) I expect AI in [knowledge area] will significantly contribute to achieving project success; (3) I expect AI will significantly impact [list of processes in knowledge area]. Section B includes general questions to cluster the sample according to the type of construction projects, demographic variables, and the respondent’s role.

The survey was administered online, from September to October 2020, following a direct connection with managers through LinkedIn and an email that was sent out to all “ENR 2020 Top 400 Global Contractors”, which is a global ranking of companies in the construction industry. Thus, the research is based on responses from practitioners in companies in different countries, for the purpose of highlighting different
perspectives also from a cultural point of view. Responses were received from 63 practitioners in 25 different construction companies based in 15 different countries (7 USA, 3 Israel, 2 Italy, 2 Spain and 1 from Australia, Belgium, Canada, Germany, Malaysia, Mexico, Peru, Singapore, South Africa, Sweden, UK). The participants include project managers (44.4%), project team members (27.0%), top managers (14.3%), project management officers (PMOs) (12.7%), and others (1.6%). They are involved in different types of construction projects, predominantly in non-residential projects (74.6%) including infrastructure projects and industrial buildings, over-ground, and underground/underwater construction projects.

Only 13 respondents (20.3%) reported that their company already adopted AI solutions. This includes 6 project managers, 3 project team members, 2 top managers and 2 PMOs, from USA (7), Belgium (3), Sweden (2), and UK (1).

B. Semi-structured Interviews
A complementary semi-structured interview was conducted to validate the survey results, gather in-depth information and understand the opinions, attitudes, and experiences of the interviewees (Rowley, 2012). It included 15 managers working in 11 different construction companies based in 9 different countries, who completed the survey and agreed to have a more detailed discussion on the topic.

The interviews were conducted via webcam, recorded, and later transcribed for analysis. In those purposeful conversations, the contents and evolution of discussions are not defined a priori, so some differences emerged among the interviews (Patton, 2014). The interviews covered the respondents’ subjective conceptualizations of AI technologies, their view on the purposes, benefits, and limitations of AI in construction projects, assessments of the key factors and prerequisites that would be considered before deciding to adopt AI technologies, and experiences related to embracing AI.

C. Findings
A total of 63 responses were used for analysis. Reliability analysis yields high Cronbach’s α values: 0.91 for the expectations of contribution to performance on the level of PM knowledge areas, and 0.96 for the expectations of contribution to performance on the level of processes within the PM knowledge areas.

The survey results indicate that AI systems are expected to be helpful in the next 10 years mainly for project schedule management (Avg.=4.16; SD=0.86), risk management (Avg.=4.03; SD=1.03), cost management (Avg.=3.97; SD=0.88) and procurement management (Avg.=3.95; SD=1.01). The knowledge area that the survey participants expected to be the least developed with regard to AI, is project stakeholder management (Avg.=3.17; SD=1.14).

Similar results were found while considering expectations for the contribution of AI to project success. AI is expected to contribute to achieving project success if applied mainly in project schedule management (Avg.=4.10; SD=0.88), integration management (Avg.=4.08; SD=0.89), risk and procurement management (Avg.=4.05; SD=0.94; Avg.=4.05; SD=0.91, respectively). Again, project stakeholder management (Avg.=3.25; SD=1.12) was perceived as the least beneficial knowledge area in which AI systems would contribute to project success.

TABLE II: INTERVIEWEES’ BACKGROUND INFORMATION

| Position                     | Company home country | Company name |
|------------------------------|----------------------|--------------|
| Project Manager 1           | Israel               | Company A    |
| Project Manager 2           | Italy                | Company B    |
| Project Quality Manager     | Spain                | Company C    |
| Project Planning Manager    | Israel               | Company D    |
| Project Development Manager | Canada               | Company E    |
| Project Manager 3           | Australia            | Company F    |
| Project Manager 4           | USA                  | Company G    |
| Project Manager 5           | USA                  | Company H    |
| VDC & BIM Manager 1         | Mexico               | Company I    |
| Head of VDC, BIM & digital solutions | Belgium               | Company J    |
| Project Manager 7           | USA                  | Company K    |

TABLE III: ASSESSMENTS OF AI CONTRIBUTION TO PERFORMANCE AND IMPACT ON PROJECT SUCCESS

| Area of Knowledge         | Contribution to performance | Impact on project success |
|---------------------------|------------------------------|---------------------------|
|                           | Avg. | SD. | Avg.  | SD.  |
| Integration Management    | 3.89 | 1.11| 4.08  | 0.89 |
| Scope Management          | 3.73 | 1.14| 3.87  | 0.87 |
| Schedule Management       | 4.16 | 0.86| 4.10  | 0.88 |
| Cost Management           | 3.97 | 0.88| 3.95  | 0.89 |
| Quality Management        | 3.89 | 1.14| 3.89  | 1.02 |
| Resource Management       | 3.84 | 0.99| 3.86  | 0.90 |
| Communication Management  | 3.84 | 1.08| 3.86  | 1.09 |
| Risk Management           | 4.03 | 1.03| 4.05  | 0.94 |
| Procurement Management    | 3.95 | 1.01| 4.05  | 0.91 |
| Stakeholder Management    | 3.17 | 1.14| 3.25  | 1.12 |
Looking into the underlying processes in each knowledge area, it is interesting to mention the processes the respondents expect AI to have a significant impact on. Those include project work monitor & control (Avg.=4.27), activity duration estimations (Avg.=4.20), schedule control (Avg.=4.19), quantitative risk analysis (Avg.=4.18), costs estimation (Avg.=4.17) and risk monitoring (Avg.=4.15).

On the other hand, the lowest-scoring processes are stakeholder engagement management (Avg.=3.06), stakeholder identification (Avg.=3.17), team development (Avg.=3.18), and team management (Avg.=3.19), stakeholder engagement planning (Avg.=3.27) and communications management planning (Avg.=3.30).

The results indicate that processes characterized by quantitative assessments are scored higher than processes characterized by human-related management practices. Overall, there are high expectations for AI applications in the next 10 years to contribute to project success by meeting project schedule, mainly through activity duration estimations and schedule control. Project risk management is also expected to benefit from AI in the near future, especially by the adoption of AI for quantitative risk analysis and risk monitoring. In addition, project cost management is likely to be influenced by AI, in particular for cost estimation and control that can positively affect the attainment of project budget goals. This is a key factor for construction projects, as profit margins are generally low (Meisels, 2020). For project integration, procurement, and quality management, the results indicate that AI could contribute the most to processes related to control, i.e., project monitor and control, procurement control, and quality control. Indeed, it emerged from the results that the processes on which AI is expected to have the most significant impact, are either estimations or monitoring and control.

Special attention should be paid to the low expectations for AI to contribute to project stakeholder management. There is little confidence in using AI when it comes to engagement of stakeholders and management of interpersonal relationships, as the human factor inevitably prevails over the technological one. Other low scoring processes, such as team development, team management, communication management planning, and resources acquisition, are also characterized by a high level of interpersonal involvement.

D. Analysis of Country’s Digital Readiness

Introducing an innovative technology like AI in PM requires a great level of commitment which goes way beyond time and money, as culture and digital maturity could be important factors in related decision-making processes (Cahyadi & Magda, 2021; Gfrerer et al., 2020). The current research sample, composed of practitioners from construction companies located in 15 different countries, enables us to analyse the results based on the digital readiness of the countries where the companies are located. The sample was divided according to the ‘Cisco Global Digital Readiness Index 2019’ (Cisco, 2019), which labels almost every country in the world according to three stages of the digital transformation: Activate stage (introducing), Accelerate stage (growing), and Amplify stage (consolidating).

The research sample was divided into two clusters, according to the stage of the country where the companies are based: Cluster AC, Accelerating Countries, which includes 33 respondents from companies located in Italy, Malaysia, Mexico, Peru, Spain, and South Africa. Cluster AM, Amplifying Countries, includes 30 respondents from companies located in Australia, Belgium, Canada, Germany, Israel, Singapore, Sweden, UK, and USA.

The following table presents the average level of expectations for each PM knowledge area, with regard to (a) AI contribution in the next 10 years and (b) its contribution to project success.

On average, professionals from AC countries tend to have higher expectations than professionals from AM countries. Specifically, significant differences were found in relation to the expected development of AI in the next 10 years to improve project integration and communication management, and to contribute to project success through processes in project scope, schedule, and communication management. This could be explained by the fact that professionals from AM countries are in a more advanced phase of digital transformation, therefore construction companies based in those countries may have a more realistic and prudent idea of where practically AI could represent a real opportunity to advance projects.
Practitioners from both clusters of countries expect AI to have the least contribution to project stakeholder management (AM=2.90, AC=3.42) and therefore will have a marginal contribution to project success, compared to all other knowledge areas. However, with regard to the highest expected contribution, there are some differences. Regarding AI contribution to project management in the next 10 years, it can be noticed how project quality management is the highest scored knowledge area for the AM group (Avg.=4.00), and it is also the only one in which AM expectations are higher than AC ones (Avg.=3.79), which could suggest that construction companies in AM countries see the introduction of AI in their projects starting from quality tasks.

E. Insights from Interviews: Opportunities

Semi-structured interviews with 15 professionals provided additional insights to explain the survey results. In general, the interviewees emphasized the support that AI can offer during the planning phase of a project and in estimating, monitoring and controlling the project during the execution phase. The interviewees mainly seek intelligent systems to connect schedule forecasts with risk estimations and cost management, as this linkage would allow them to keep track of the work progress and make changes in real-time without having any financial issues that could undermine project success, hence profit margins. As these profit margins are low in the construction industry, managers highlighted the fact that having costs under control is vital not only for the project but for the whole organization as well.

One of the main reasons to adopt AI is related to improved efficiency, as described by an interviewee from Company I in Belgium, where machine learning tools are already applied for document analytics: “[It] uses machine learning to autonomously look for information in project documents to make analytics, and here the advantage is that there are less mistakes due to oversights and people who should do analytics have more time for other activities”.

An additional major perceived advantage of using AI is to advance quality procedures. For example, an interviewee from Company G in the USA that has requested a beta version of software using computer vision which is able to track quality deviations on drywalls with the support of BIM, said “As for quality check, there’s a software [...] allowing you to walk around with a 360° camera on your helmet [...] for production and deviation tracking of certain traits in BIM, and they are starting out with drywalls. We requested to get full access to this beta version, so that we can test it [...] hopefully starting from 2021.” This line of thinking was further stressed by a project planning manager from Company C in Spain: “We have been using technologies like BIM that could work really well with AI. […] we don’t use BIM as a standard in the design phase only, as we are using it to manage the construction phase too. This is important because AI could fit very well with BIM, in my opinion.” and by a colleague who serves as a project quality manager: “I could see AI systems replacing site supervisors for inspections [...] using a drone from remote to inspect the construction site, collecting information through sensors and cams and forwarding them to the BIM in real time, which would process and elaborate the data providing reports, documentations and updates regarding the work progress. […] but for now, this is pure utopia”.

Another interesting insight is related to the role of AI in knowledge areas and processes that involve a high level of human relationships and people engagement. The survey results indicate that stakeholder and communication management are among the knowledge areas that are not expected to benefit a lot from AI in the next few years. In fact, many interviewees stated that the construction industry is all about cultivating relationships with both internal and external stakeholders. Although they have no doubt about the ability of AI software to support team management, communication and stakeholder engagement, they refuse to give up such processes to AI, as they believe the lack of human interactions would lead to lower levels of efficiency and effectiveness. In this sense, they perceive AI as a solution for other parts of the project, to free up time for communication and engagement.
activities. For example, an interviewee from Company E explained that “[...] people in the company are still quite resistant to taking orders from a machine. [...] if you’ve got a computer with a voice telling you “make this offer” you are less likely to receive a positive feedback from it. [...] Construction, at the end of the day, is a people business. [...] A lot of construction relationships are based on relationships not between companies but between individuals in those companies, based on your history and reputation. That is the type of thing I do not think AI can replace, [...] if I had AI to take care of my schedule, forecasting, costing and all those quantitative analyses, I would be focusing on building and developing my relationship with the client, stakeholders, estate team and things like that.” A project manager from Company A said that “I think I would give more time to people relationship management, which must be done in person, whether it is with workers, project team or project stakeholder.” A representative from Company H added that “[...] having more time to actually dedicate on meetings, building relationships and communicating to each other would be very useful for the overall project.” It was nicely summarized by an interviewee from Company C who shared his opinion on the matter, saying that “[...] AI will never be able to fit for each and every task and process in the project management, since people relationship is important in construction industry. [...] more time to better manage and coordinate different teams and departments, improving communication towards and among them, so that everybody in the project is kept posted, avoiding additional problems and conflicts.”

F. Insights from Interviews: Challenges

Only two out of the eleven companies represented by the interviewees have already adopted AI to support project management. The first one (Company I) is currently using AI applications to generate analytics out of information in documents and reports, and by applying computer vision to reduce waste material in construction sites. The other one (Company G) is using AI technology that analyses project specifications, creates a list of completed submittals, and based on computer vision software detects safety issues through a stream of pictures and videos. The remaining companies have not adopted AI solutions yet. An in-depth examination of the reasons yielded a list of factors that can be divided into two categories: internal (company-related) and external (industry-wide).

TABLE V. BARRIERS TO ADOPTING AI IN CONSTRUCTION PROJECT MANAGEMENT

| Internal (company-related) | External (industry-wide) |
|----------------------------|--------------------------|
| Corporate culture          | Technological aspect     |
| Digitization immaturity and data logistics | Solutions in the market |
| Lack of product awareness  | Legal/ethical aspect     |
| Financial aspect           | Country and culture      |
| Lack of knowledge and skills |                          |
| Implementation effort      |                          |

The internal barriers to adopt AI technologies derive from the challenges to introduce an innovative technology that requires a great level of flexibility across the whole organization, an open mindset, and an ambitious long-run perspective. However, many construction companies lack these aspects in their organizational culture and are behind in the digital revolution, in terms of digitization and data logistics, which are critical for AI. Moreover, AI is perceived by many managers as a theoretical field that still needs to be explored in order to develop market-ready solutions. Although some AI software are already available in the market, most construction companies are not aware to that, hence find it difficult to appreciate the potential benefits. In addition, AI requires a considerable funds investment that not many construction companies are willing to make, especially when considering the low-profit margins that characterize the industry. Those factors are added to the current lack of knowledge and skills among employees in construction companies on one hand and on implementation challenges on the other hand. Since AI is an innovative and complex field, not many people have neither the basic knowledge nor the skills to deal with it in their daily jobs. It is further reinforced when coming to the implementation phase, where there is a need for a group of people who are not only knowledgeable but also agree to dedicate time to implement AI and to manage the change process that comes with it while involving different teams and departments.

External barriers to adopting AI technologies are related to the nature of the construction industry, which is known as a low-tech industry. In general, technological innovations are very slowly accepted by construction practitioners, while AI is a dynamic evolving technology. Due to the central role that human relationships play in construction projects, any AI solution that could somehow affect the more “human” part of the job is off the table. It raises many concerns in relation to the proper legal framework to apply when dealing with an enormous quantity of data and like in other industries there are still unresolved issues of privacy and intellectual property. Also, the available AI solutions are considered insufficient for the requirements of construction projects. Exclusively to underground construction projects, the levels of unpredictability and required adaptivity are very high, thus it would be necessary to provide an ad-hoc AI solution for each different project, which is neither convenient nor feasible. Another factor perceived as a constraint is related to global construction projects. No matter how open the culture of the home country is toward change and adoption of AI, its use is not always guaranteed if the international market is not ready for it. Many suggested how it should be the project’s client (i.e., government, a company, etc.) to demand it, otherwise, the risk could be to invest in a new technology that is not valued as a point of difference with respect to competitors’ offer. Indeed, it is also important to consider the country where a project is executed, as in many international projects there is a need for collaboration with local partners that have great bargaining power when setting the policies and might be reluctant toward the adoption of AI.

V. DISCUSSION

The current explorative study provides insights on developing trends of applying AI in construction projects. It is based on a mixed research method where a survey and semi-structured interviews were applied to identify future potential AI applications in each one of the PM knowledge...
areas and related processes. The results indicate that AI applications will be most beneficial for improved decision-making by reducing errors and mistakes that nowadays occur due to incomplete information and human imperfect analyses. Through the integration of AI applications, the processes related to the ‘iron triangle’ or ‘triple constraints’, i.e., schedule, cost, scope, and quality management, jointly with project risk management, are expected to have a major impact on project success. These results are in line with prior research on AI in engineering and construction, which mainly highlighted budgeting and cost management (e.g., Cheng et al., 2015; Kamooma & Budayan, 2019), and schedule management (e.g., Faghihi et al., 2015). Although risk management as a specific knowledge area for AI applications was rarely studied, the concept and implications of uncertainty are repeatedly mentioned in this context. Like in other industries, construction project managers expect to see the benefits that AI could bring to quality and productivity (PMI, 2019) which will lead to better financial results.

The challenges to adopting AI technologies, as emerged during the interviews, turned out to fit with the Technology-Organization-Environment framework presented by Hofmann et al. (2020). The impeding factors presented in this study fall in the technology domain (technological aspect, lack of knowledge and skills, and digitization immaturity and data logistics), the organization domain (financial aspect, corporate culture, and implementation effort) or the environment domain (solutions in the market and legal/ethical aspect). In this sense, these factors represent pivotal elements that could undermine the adoption of AI in PM at an early stage of the decision-making process.

However, as the results of the current study imply, the adoption of AI technologies in construction projects, is also influenced by a wider perspective that takes into consideration the digital readiness of the country in which the companies are based. Analysis of expectations to use AI technologies in different countries reveals that companies in the amplified stage, generally represented by developed economies, are in a better position to adopt AI, however, they are slightly hesitant to think this will happen any time soon. This additional factor will probably impact which companies will decide to integrate AI in the management of projects and therefore will probably have a competitive advantage over other companies in the rapidly evolving international construction business (Utama et al., 2016).

Overall, there are many concerns related to future human interactions with innovative AI technologies, derive from questions on trustworthiness, privacy issues, and the reluctance of senior employees in the industry. Nevertheless, managers are open to accepting and embracing technologies that will improve their work as leaders. It is in line with previous studies that argue that technology can help project managers to promote performance, team development, and competency (Anantatmula, 2008) and that many of the currently managerial tasks will be efficiently completed by cognitive intelligent applications, while project managers will apply advanced emotional intelligence and social intelligence competencies (Kaplan & Haenlein, 2019). Managers of construction projects show interest in spending more time coordinating workers, managing teams, and engaging with the project’s client and other stakeholders. In this sense, knowledge areas like project stakeholder and communication management, which are the least expected to be improved by AI, could benefit from it indirectly.

VI. CONCLUSIONS

This study investigated the possibility of AI becoming a game-changer in managing projects in the construction industry. By analysing the expectations of 63 practitioners from different construction companies around the world, it can be concluded that AI is considered a solid solution for the improvement of work processes and contribution to project success in almost all PM knowledge areas, especially in the estimation and control processes for project scope, schedule, cost, and risk management. Differences in expectations were identified when considering the sample’s clusters by country’s digital readiness, whereas practitioners from companies based in accelerating countries tend to have higher hopes than the ones in amplifying countries, probably because the latter consider AI as a valid option to improve PM practices but are aware to consequential complications and consequences.

The most challenging area in adopting such technologies is related to the human perspective. It raises concerns about trust, privacy, the possibility to take over some of the project managers’ roles in their interactions with various stakeholders, and anticipations that their colleagues, mainly senior managers, will be reluctant to major changes. However, additional impediments on the company level (such as corporate culture, lack of skills and knowledge, and required implementation efforts and funds) and on the industry level (such as legal issues, technological readiness, and available solutions) hold back the integration of AI applications in projects. It must be noted that currently, there are very few AI solutions for the management of construction projects available in the market, mainly for document analysis, remote analysis of construction sites, collaboration with subcontractors, and forecasting. However, those applications provide partial solutions, and it can be safely anticipated to see more mature and comprehensive solutions in the near future.

This research is not free from limitations. First, the sample size is relatively small, thus generalization of the conclusions should be taken cautiously. Although the findings from the survey were confirmed by the interviews, future works could investigate this topic based on a larger and more differentiated sample, both in terms of respondents’ positions and geographical distribution and by considering additional variables such as the size of the company or type of project. Second, this study aimed to capture the expectations of project professionals, therefore assuming their knowledge of relevant AI technologies and techniques is limited. An additional study that will incorporate project professionals on one hand and AI experts, on the other hand, might enable recommendations on appropriate AI techniques to respond to project needs. Finally, this study is explorative and was aimed to identify and analyse expectations for AI in construction projects. As AI technologies are developing rapidly, there is a need for a continuing study to characterize the actual solutions AI can provide to successful projects.
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