The Intersection of Artificial Intelligence and Project Management in UK Construction: An Exploration of Emerging Trends, Enablers, and Barriers

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Abstract

This paper delves into the transformative impact of Artificial Intelligence (AI) on project management (PM) within the UK construction industry. Our research unfolds in two main dimensions: firstly, examining the current applications of AI in this sector, and secondly, evaluating the challenges that hinder its broader adoption, alongside the potential benefits it offers. Central to our study is the role of AI in enhancing productivity, which is crucial for understanding the factors that influence AI integration in the construction industry.

Keywords: Project Management, Artificial Intelligence, Construction Industry

Introduction

The UK construction industry is a long-term laggard of productivity in UK industry (ONS, 2021). PM plays a crucial role in the UK construction industry driving success. PM provides a structured framework helping to deliver projects on time, within budget, and to the desired quality (Al-Mhdawi, O'Connor, et al., 2023; Mohamed et al., 2024). However, it is not just about managing tasks; it's about leading teams, managing risks, and ensuring stakeholder satisfaction (Al-Mhdawi et al., 2024; Antonopoulou & Dacre, 2021; Dacre, 2024; Dacre, Eggleton, Cantone, et al., 2021; Manh et al., 2024). This includes fostering effective communication across diverse teams and maintaining a focus on sustainability and innovation (APM, 2023; Dacre, Yan, Frei, et al., 2024; Dong et al., 2021a; Gkogkidis & Dacre, 2020b, 2021; Tite et al., 2021a). Yet, despite of the role PM plays, only half a percent of megaprojects is delivered on time, on budget and delivering the intended benefits (Dacre, Eggleton, Gkogkidis, et al., 2021; Eggleton et al., 2021, 2023; Flyvbjerg & Gardner, 2023).

In this context, this research aims to answer the following research questions (RQ):

(RQ1) What are the main areas (emerging trends) of use for AI in the UK PM industry currently?

(RQ2) What are the enablers and barriers to adoption of AI technology in PM within the UK construction industry at the time of this research?

This paper delves into the potential transformative impact of AI on PM within the UK construction industry (Dacre & Kockum, 2022a, 2022b; Dacre et al., 2020; Gong et al., 2022). The research unfolds in two main dimensions: firstly, examining the current applications of AI in this sector, and secondly, evaluating the challenges that hinder its broader adoption, alongside the potential benefits it offers (Hsu et al., 2021a; Kockum & Dacre, 2021). Central to the study is the role of AI in enhancing productivity, which is crucial for understanding the factors that influence AI integration in the construction industry (Al-Mhdawi, Qazi, et al., 2023).

Theoretical Context

In this research AI is defined as "the designing and building of intelligent agents that receive precepts from the environment and take actions that maximize its chance of successfully achieving its goals" (Russell and Norvig, 2010, p.8).

Pan and Zhang (2021) assert AI technologies improve existing practices as they become more automatable and objective. In particular, they refer to Machine Learning (ML) being applied to the mass of accumulated data for hidden knowledge discovery (Hsu et al., 2021b). Arthur Samuel is widely cited as a pioneer in Machine Learning, describing it in 1959 as 'Machine Learning is a field of study that gives computers the ability to learn without being explicitly programmed' (Gogas and Papadimitriou, 2021) and the definition hasn't dramatically changed over the years with another commonly cited definition being "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E." (Mitchell, 1997, p.2).

Levit and Kunz (1987) proposed that AI could be used to browse databases and identify information that could be used to support the development of project objectives and other information relevant to a specific project, citing that this is 'often undertaken through the memory cells of experienced project managers'. With the emergence of generative AI and natural language processing tools, such as Chat GPT, data analytics is starting to be used to identify relevant information from the available datasets, supporting the claims made by Levit and Kunz; albeit this is a very recent development and not widely observed directly within project management processes (Al-Mhdawi, Qazi, et al., 2023; Baxter et al., 2023; Brookes et al., 2020; Dacre, Yan, Dong, et al., 2024; Xu, 2023).

In 1998 researchers conclude that a framework would be created using product modelling, workflow management, logistics, and artificial intelligence, which would reduce the pre-construction period (the activities required to be undertaken prior to commencing on site) by 50% (Scherer, 2005). A recent survey indicated that Project Professionals thought that AI would positively impact the project management profession in assisting in decision making; stronger cyber security; producing more consistent and/or timely reports; and freeing up time for construction project professionals to work on more strategic areas of the job (APM, 2023).

Whilst there are some industries and sectors that have benefited significantly from the introduction of AI technologies, such as the automotive industry and the retail sector, the construction sector remains slow to adopt new technologies, including AI (Dacre, AlJaloudi, et al., 2024; Dacre et al., 2019). The construction industry is a complex sector with multiple reasons for the slow uptake in available technologies (Al-Mhdawi, Dacre, et al., 2023; Sonjit et al., 2021b; Tite et al., 2021b). High levels of legislation, the coordination of multiple skills and professions involved and the relatively low levels of research and development investment within the industry are all cited as potential barriers to adoption (Babič and Rebolj, 2016). A recent produced by report by Forbes showed that the adoption of AI in Construction remains behind many other industries (Hooson, 2023). The construction industry is one of the sectors with the lowest level of adoption of AI in 2020 (Javed et al., 2018). Figure 2 shows the rate of AI adoption by sector in 2020 in the UK.

This is further evidenced in a report produced by McKinsey (Chui, 2017), not only indicating that the adoption of AI in the Construction sector is one of the lowest in terms of adoption, but also predicts the least amount of investment between the years of 2017 and 2020.

Armstrong et al. (2023) states that the Construction industry is starting to embrace the power of technology, with 40 percent of Engineering and Construction firms adopting artificial intelligence with data analytics considered to be one of the areas which has the greatest potential. This is further supported by Regona et al. (2022) states that construction companies are starting to explore the adoption of AI with a view to streamlining processes, increasing productivity, and improving cost overruns, improvement in site safety and increased management efficiency of project plans.

It has been suggested that AI has not yet been greatly adopted in project management but that the profession will be forced to change to accommodate the adoption of AI as the technology emerges and clear evidence of its benefits are observed (Belharet et al., 2020). This position is supported by the research, specifically when reviewing AI in project management within the Construction Industry (Dong et al., 2022). There is evidence of adoption in wider management functions in a report by published by Forbes in 2021, stating that 66% of business leaders have benefitted from AI in their decision making (Elliott, 2021) with the report going on to say that the three main areas of use were Machine Learning, computer vision (CV) and natural language processing (NLP).

Cubric (2020) identified that the most significant barriers to successful AI integration included data quality and management, resistance to change, and a lack of understanding and trust in AI. The most prevalent barriers to adoption cited in the consulted literature included human barriers, technical and budgetary constraints. The most prominent barrier to adoption appears to be related to the existing project management community's reluctance to embrace AI technology, either through fear, lack of knowledge or uncertainty. A report by Forbes stated that the three biggest concerns that the British public have regarding AI is over dependence on AI, loss of human skills, and autonomous AI systems making decisions without human intervention (Hooson, 2023). As such, the barriers to adoption within the construction industry are aligned to those generally experienced in society.

Alshaikhi and Khayyat (2021) claim that a combination of human skills and AI technology will be required to achieve a positive outcome and that Project Managers should develop their skill in areas that AI cannot achieve the desired outcome. This position is further supported by research undertaken by Gil et al. (2021) who concluded that the limitations and weaknesses of AI in project management require the Project Manager to use their experience when evaluating results.

Projects by their very nature are unique and project organisations are considered to be complex and unpredictable (Barber et al., 2021; Dacre et al., 2022; Dong & Dacre, 2024; Dong et al., 2024; Sonjit et al., 2021a). Construction is also known to be complex involving multiple facets of work and multiple project team members (Dacre et al., 2018; Dong et al., 2021b). Combine the two and it explains one of the reasons why the majority of the project management community struggle to understand how automating project management can be achieved, believing that AI can mainly assist with simple processes, factual, pre-determined matters (Eber, 2019; Eber, 2020).

Skinner and Williams (2022) support that view stating that 68% of companies believe that AI will change the role of the Project Manager in the next 3 years, indicating that AI has not yet changed the role at the time of this research. El Khatib and Falasi (2021) say that 'In the future, AI will not be a choice for Project Managers but will be an integral part of their strategy for survival'. They cite one barrier to adoption as the manager's lack of understanding of how AI can affect their organisation's operations.

APM (Dacre and Kockum, 2022) concluded that whilst most project professionals believe that AI will change the project management profession, there was ambiguity in what the impact will be. The research also concluded that whilst the demands of AI on Project Professionals was perceived to be high, the training being received was low. Wang (2019) observed that the root cause of the problem is that people don't know how to use AI technology properly in project management.

Technical Barriers relates to the lack of consistent datasets in construction is preventing Machine Reading Comprehension models to be trained with data and knowledge acquisition issues as further limiting factors (Abioye et al., 2021). Parnell and

Stone (2022) reinforce the issue regarding the availability of data. The article states that ‘AI thrives in the world of big data. AI needs big volumes of data, bigger than currently used in megaprojects.

Financial Barriers involve reduced budgets as a limiting factor for the adoption of AI in project management, recognising the expense of implementing and maintaining AI systems (APM, 2023). However, there is no supportive evidence in either case that provides any insight into this challenge and therefore, little evidence of this being a key factor.

Other challenges steams from the lack of legislation associated with AI. There are many issues ranging from social economic concerns, such as job losses, harmful use of AI and the transparency of algorithms, which in some sectors would be critical - such as in the health and care sector (Haenlein and Kaplan, 2019). The uniqueness of projects and the variables associated with project management require a substantial dataset to be analysed to make useful predictions and analysis. As there is no agreed open-source standard for construction data, this is a significant issue. Profit making organisations are in a race to gather data for their own personal gain and are understandably reluctant to share the data with competitor organisations. Not for profit organisations such as the Construction Data Trust (https://www.datatrust.construction/) are trying to establish an open-source dataset for the benefit of the UK construction industry, as are the UK government, who are establishing a new benchmarking service (https://ipa-benchmarking-data.service.cabinetoffice.gov.uk/) which will be underpinned by public sector project data. The risk of a security breach and shortcomings associated with sustainability (Taboada et al., 2023)

Skinner and Williams (2023) indicate that 56% of respondents of their survey cited uncertainty about the value add as a barrier for adoption. They also quote the high cost on implementation as a barrier to adoption along with the fact that decision makers are likely to be uncertain about the value, however, the paper lacks details on the costs so it is not possible to support that particular proposition.

Research Approach

Due to the research exploring the emergence of new ways of working within the construction industry, an inductive approach is employed anchored in a qualitative framework for data collection (Reynolds & Dacre, 2019). This methodology is selected due to the exploratory nature of our research, which investigates emerging practices within the UK construction industry (Easterby-Smith et al., 2018). In order to delve into the nuanced perspectives, interpretations, and experiences relating to the adoption of AI in project management, semi-structured interviews were adopted as the primary method of data gathering (Bryman, 2016).

We employed a targeted sampling approach to ensure the inclusion of experienced senior project managers from a diverse range of organisations operating in the UK construction industry (Patton, 2015). Interviewees were specifically selected based on their role titles or equivalent positions as 'Head of Project Management'. This strategic sampling allowed for the capture of insights from individuals with extensive experience and decision-making authority within their respective organisations (Creswell and Poth, 2018). Eleven interviews were conducted, with each interviewee represented as R1-R11 in Figure 1, along with their years of experience. The interviewees' experience in project management ranged from 8 to 30 years, with an average of 18 years. This diverse range of experience provided detailed perspectives, ensuring that the findings were not limited to a narrow subset (Guest et al., 2006).

N. of Services Offered	Small (S)	Medium (M)	Large (L)
L			R1(25), R2(20), R4(30) and R10(14)
M	R3(16) and R7(17)	R5(8) and R8(24)	R9(25)
S	R6(8) and R11(10)		
	Size of Organisation		

Figure 1 – Size and service proposition of organisations (years of experience of interviewee)

The interviewees spanned a variety of organisational contexts within the UK construction industry, ranging from smaller, specialised project management firms with fewer than thirty staff, to expansive, multi-disciplinary engineering companies employing over forty thousand individuals. This diversity in organisational size and structure was crucial in providing a broad and varied insight into the barriers and enablers AI presents in project management across different professional settings (Dacre et al., 2014; Yin, 2018).

Semi-structured interviews were conducted, allowing for a balance between predetermined questions and the flexibility to explore emerging themes and insights (Gkogkidis & Dacre, 2020a; Kvale & Brinkmann, 2015). The interview guide was developed based on the research questions and the key themes identified in the literature review, including the current applications of AI in project management, the enablers and barriers to AI adoption, and the potential benefits of AI integration (Rubin and Rubin, 2012).

Data analysis followed an iterative process, consistent with the inductive approach employed in our study (Strauss and Corbin, 1998). Interview transcripts were initially coded using open coding, which involved identifying and labelling segments of data that were relevant to the research questions. These codes were then grouped into broader categories and themes through a process of axial coding, which involved identifying relationships and connections between the initial codes (Charmaz, 2014). Emerging themes were continually refined and revised as new data was collected and analysed, ensuring that the findings remained grounded in the experiences and perspectives of the interviewees. The use of constant comparative analysis allowed for the identification of similarities and differences across the interviews (Glaser and Strauss, 1967).

Results and Discussion

Our study reveals critical insights into the current state and potential future of AI in project management within the UK construction industry. The findings from our empirical data, summarised in Table 1 and Table 2, addressing RQ1 and RQ2 respectively. There was greater emphasis on human barriers to the adoption of AI in project management emerging form the empirical data, while financial and technological barriers were also a concern amongst the interviewees, the data was less conclusive. In the financial technological space, data and information security, and business risk associated with data ownership were noted as areas of great concern and barriers to AI adoption.

Table 1 – Main areas of use for AI and future expectations reported by interviewees.

Main areas of use of AI in PM amongst interviewees
All respondents: Currently limited use in an exploratory fashion. Examples include chatbots, data analytics and generative AI for proposal writing. No specific examples in the project management areas of work. *R1, R9, R10 and R11:* The organisations where these interviewees work are currently developing AI policies, which in general lines contain restrictions on uses of AI while further investigation takes place.
Future expectations
Increase efficiency/ productivity: There is an expectation that AI will increase productivity over the next few years, particularly regarding tools and tasks, as well as administrative processes. A common vein of thought amongst interviewees focused on increasing efficiency through the use of AI in administrative tasks and processes, freeing up time for project managers to concentrate on more difficult to be replicated aspects of the job, such as, people management, relationship management and all other aspects of the job that require personal skills. Despite of the overall optimism from interviewees, one of the respondents (R11) expressed a less optimistic view, suggesting that as stands, they can't see AI making a significant impact on the overall design process. *Quality Improvement:* Another area where several interviewees expect to see a contribution when AI is adopted more widely is in quality improvement, but the data lacked specific examples in this space. *Timeline for significant adoption of AI in PM:* While majority of the respondents (6) expect to see significant adoption of AI in PM between 3 and 7 years, 4 respondents predict an early impact (1-3 years), with only one respondent stating that it will take 7 or more years before significant adoption is observed.

Table 2 – Human Barriers to adoption of AI in PM within the UK construction industry.

• Association of Adoption of AI with job insecurity and the perception that AI tool could replace human workers in a variety of tasks. • Lack of trust in the technology • A perceived lack of transparency of some AI systems. • Skills gap/ lack of training. • Concerns related to future development of junior staff.

The findings from our empirical data suggest that AI's emerging role is characterised by experimental applications, with its potential hindered by various barriers such as the lack of training and organisational reluctance. However, growing understanding and technological developments are acting as significant enablers for its adoption.

First, our research indicates that the majority of AI systems and applications in construction projects are currently in an experimental phase, leaving their value proposition largely unverified (Belharet et al., 2020). Moreover, our findings suggest that the emerging skillset in AI, combined with the general lack of training and understanding within organisations, poses a significant barrier to its adoption (Dacre and Kockum, 2022). Therefore, the uncertainty regarding the practical application and value of AI in projects is a key barrier, highlighting the need for a clearer understanding and validation of these technologies (El Khatib and Falasi, 2021).

Second, our research underscores the promotion of validation protocols to enhance security measures. Creating standards for AI integration within existing project management tools and processes. These measures are crucial to alleviate the prevailing scepticism surrounding AI security and adoption in projects (Taboada et al., 2023). Our findings align with assertions concerning the potential benefits of AI, which are yet to be fully realised in practical applications (Regona et al., 2022)(Zhang et al., 2023). Our findings also suggest that the lack of consistent datasets in construction is preventing Machine Reading Comprehension models from being trained with data and knowledge acquisition, further limiting AI adoption (Abioye et al., 2021). Thus, the transient and unique nature of projects and associated variables require a substantial dataset to be analysed to make effective predictions and analysis (Parnell and Stone, 2022).

Third, there is an increasing general understanding of AI in the sector, and the consensus among our interviewees was that the significant adoption of AI technologies within projects and construction is imminent. This trend is regarded as foreseeable, considering the continuous developments of AI and its potential benefits (Armstrong et al., 2023). The growing awareness of AI's capabilities in less quantitative areas, such as procurement and knowledge management, indicates that the general level of understanding of AI capability is increasing (Holzman et al., 2022).

Finally, our empirical data confirm that AI may add value to project management. The barriers identified in our study align with the findings from our literature review, encompassing human, technological, and financial aspects. The most prominent barrier to adoption appears to be related to the existing project management community's reluctance to embrace autonomous AI technology, either through concerns, lack of knowledge, or uncertainty (Hooson, 2023). Financial barriers, such as reduced budgets, are also recognised as a limiting factor for the adoption of AI in project management (APM, 2023).

Conclusion

The construction industry's engagement with AI technology presents a paradoxical model. For instance, despite the benefits garnered by sectors such as automotive and retail, construction remains reticent in adopting AI innovations. This reluctance may be attributed to a confluence of factors; the sector's complex legislative environment, the requirement for coordination among diverse professional skills, and a relatively subdued investment in research and development (Babič and Rebolj, 2016).

Our research thus highlights the significant potential of AI in project management, underscored by emerging trends and enabled by technological progress and growing sector awareness (Gkogkidis & Dacre, 2023). Although, overcoming identified challenges, including human, technological, and financial barriers, is a salient aspect for realising this potential (Dacre et al., 2015). These present significant challenges that warrant further examination in order to facilitate the broad acceptance and implementation of AI in the construction sector in the UK. Hence, we argue that surmounting these barriers is crucial to achieving widespread AI adoption in construction project management. However, considering the complex nature of these challenges, the timeframe for extensive AI integration within the construction industry remains uncertain.

Whilst our research provides valuable insights, there are a number of limitations. Firstly, the qualitative nature of our research, based on semi-structured interviews with a targeted sample of senior project managers, may limit the generalisability of our findings. Secondly, the rapidly evolving nature of AI technology means that the findings of this study may not fully capture the most recent developments and their potential impact on project management practices. Thirdly, a notable point from the interview process was the potential bias in the responses, as respondents were asked to discuss barriers relating to human, technology, and financial elements.

As such, future research could explore several themes to further advance our understanding of AI in project management within the construction industry (Pontin & Dacre, 2024) Our findings align with assertions concerning the potential benefits of AI, which are yet to be fully realised in practical applications (Sonjit et al., 2021c). For instance, by engaging in a larger-scale, quantitative study, this could afford more generalisable insights into the adoption and impact of AI across the sector. Additionally, a longitudinal study could be undertaken to track the evolution of AI applications and their effects on project management practices over time. Finally, a comparative approach across different countries or regions could also highlight any potential influences of cultural, regulatory, and economic factors on AI adoption in construction project management.

In summary, our study contributes to the ongoing discourse on AI in project management by undertaking an exploratory investigation of its existing status and prospects in the UK construction sector, thereby creating a foundation for further investigation and practical exploration in this evolving domain.

Acknowledgments

The authors would like to thank all interviewees for their time and contributions.

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