The Chartered Institute of Building

CIOB Artificial Intelligence (AI) Playbook 2024

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Foreword

It feels fitting that in the year in which CIOB marks our 190th anniversary, we publish a new playbook to examine a technological advancement with the potential to transform our industry. In this playbook, following our first ever global conference focussed on AI earlier this year, we look at what artificial intelligence might mean for the future of construction.

At CIOB, our work to act in the public interest leads us to focus on the issues of the day, which currently include:

- promoting best practice to drive environmental sustainability,
- highlighting the need to deliver quality and safety and
- encouraging a range of measures to tackle the skills gap.

It could be argued AI can make a significant positive difference in all those areas.

Our current corporate plan also talks about new technologies being widely adopted where they provide benefits for the industry and those working in it. It is highly likely AI could be deployed to have a positive impact in the short-term on both the skills gap and the need to drive improvements in sustainability, using digital tools to push our industry forward in much-needed ways.

There are many areas where AI could become an integral part of the process. What AI could do for the design and planning of our buildings, towns and open spaces could be transformative.

In this new playbook, our experts set out what AI is, why it is important to construction and how it might usher in opportunities for contractors and the wider industry. It covers the breadth of the potential areas where AI could be deployed, including how to leverage it in your workflows, how it could impact on contracts and mitigating risks and, importantly, the considerations you should take in your mindful AI journey.

It is my hope the "CIOB Artificial Intelligence Playbook" will go a long way towards helping construction professionals understand AI in the context of our sector.

I would like to thank the CIOB Digital & Innovation Advisory Panel and their specialist AI Working Group for creating this playbook. I am always grateful to the experts within our community who contribute their knowledge and experience, collaboratively bringing the best thinking to industry advancements.

Caroline Gumble – (Dr) BSc (Open), CMS, MCIPD, FRSA, MIEx, HonMCCM
CEO, Chartered Institute of Building

Acknowledgements

This playbook has been created with a series of insights on key AI themes and forms a set of distinct vignettes which can be read individually or collectively. The chapters have been arranged in a logical sequence, but they also stand on their own. This work builds upon the discussions from CIOB's AI Conference, where both our CEO, Caroline Gumble, and Eddie Tuttle, our Director of Policy, Public Affairs & Research, spoke and contributed to advancing this agenda.

CIOB has a dedicated Policy, Public Affairs, and Media Relations team that has helped bring this playbook together. We appreciate the commitment of the Digital & Innovation Advisory Panel, whose expertise enables us to have a prominent voice on this important agenda.

CIOB would also like to extend its gratitude to the following contributors:

David Philp – Cohesive

With over 30 years in industry David is a Chartered Construction Manager by background. As Chief Value Officer at Cohesive he is responsible for driving customer-centricity and creating sustainable value and impact for asset owners and operators across their asset lifecycle and portfolios.

David has been involved in delivering many innovative programmes, digital change strategies and digital asset management strategies across the globe from UK, Hong-Kong, Singapore, Australia, and the Baltics.

He was seconded in the UK Cabinet Office in 2011 as Head of BIM Implementation and has been a key contributor to the UK public sector BIM mandate (GCS 2011-2016) he was also Chair of the Scottish BIM Delivery Group through the Scottish Futures Trust delivering the BIM requirements of the Scottish Government.

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Stefan is a chartered Architect, Construction Project Manager, Consultant, and published author. He is Senior Program Manager for Education and Partnerships at Bentley Systems. He was a founding member of the CIC BIM 2050 group and sits on several industry and technical standards committees, including the Architects Council of Europe (ACE) BIM Working Group. Currently, he serves as the Vice Chair of the CIOB Digital & Innovation Advisory Panel.

Stefan is co-author of several books and is privileged to have won awards from CIOB, Leeds Beckett University, Generation for Change G4C, and Constructing Excellence in recognition of his contribution to the construction industry.

Acknowledgements

Alex Luketa – Xerini

Alex, Chief Technology Officer and Co-Founder of Xerini Limited, leverages a distinguished career in top financial institutions such as Morgan Stanley, Goldman Sachs, and JP Morgan to address unique technological challenges across various sectors. With a focus on enhancing business productivity through bespoke solutions, Alex's leadership at Xerini has fostered key partnerships with major clients like HS2 and National Highways, driving advancements in data utilisation and system integration. Alex's strategic vision and agile methodology champion long-term partnerships and continuous adaptation to client needs, securing Xerini's role as a pivotal player in technological innovation and business optimisation.

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Dr Saleeb is Associate Professor in Creative Digital Technologies & Construction at Middlesex University, and Programme Leader for the MSc Building Information Modelling Management programmes. Through her position at the university and on several professional body steering committees, she provides consultation for both industry projects and organisations in sustainable design, construction, digital transformation, BIM, Digital Twins, AI and onsite project management.

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May is the Global Director of Commercial, Legal and Digital Risks at international engineering firm, Buro Happold. May is a senior construction lawyer of over 19 years' experience and is recognised as a leading legal specialist in digital and construction technology. May has led the drafting teams of various documents in this field, including the ISO19650 protocol templates and guidance. She is one of the co-authors of the Centre for Digital Built Britain's Digital Twins Roadmap and Digital Twins Toolkit Report, and a member of the Working Group for version 2 of the UK Government's Construction Playbook.

Murillo Piazzi – Okana

Murillo is a senior digital consultant, having authored training programmes such as BIM for health and safety, Understanding COBie and Understanding IFC. He is also a lead assessor for ISO 19650-1 and 2 and has supported organisations to establish and fulfil information management requirements. Murillo's aim is to link academia and industry, sharing his knowledge with others.

Paul Thorpe – Okana

Paul has worked globally across multiple large-scale projects ranging from airports, data centres, hospitals, and commercial skyscrapers. He brings years of experience in digital management of construction projects and defining digital transformation strategies. Paul is driven by maximising the value of digital adoption in the construction industry. He has worked across industry sectors and has specialisms in Information Management, BIM Execution and Digital Transformation.

Prof. Bimal Kumar – University of Strathclyde

Professor Kumar has had a distinguished and extensive career in the field of computer-based design and construction research. He initiated his research journey with a PhD in Artificial Intelligence applications in Structural Design from Edinburgh University in the 1980s and has maintained a dedicated focus on this thematic area throughout his career. Over the years, he has established significant collaborations with leading research centres worldwide, including Stanford and Carnegie-Mellon Universities in the USA, NUS (Singapore), and the Hong Kong University of Science and Technology.

Acknowledgements

Vicki Reynolds – Catalyst & Obi

Vicki heads up information security and technology strategy and implementation at Catalyst. During her career in construction, she has held roles in information management, BIM management and digital construction across several high-profile projects, delivering digital solutions, implementing new technology, and upskilling individuals and organisations.

An active member of the construction community both locally and globally, Vicki has written and delivered workshops and lectures on digital construction and information management for audiences in the UK, Ireland, Germany, the Netherlands, Canada, India and China.

Charlene Burkmar – Vision into Reality

Charlene is the managing partner of Vision into Reality, a consultancy established to offer the end-to-end capability that enables successful change. She and her team offer objective support in the creation of business and digital, strategies and plans, embedding the change throughout the organisation, for long-term sustainable success.

She has spent her career working with government agencies and commercial companies across the globe to create and entrench their digital transformation, business and growth strategies.

Introduction

Data is increasingly being treated as a strategic asset in the construction industry, by supporting insight, decision-making and enabling increasingly digital and automated ways of working. Digital workflows and data are also pivotal to the future of our profession, bridging the skills gap, enabling modern methods of construction and encouraging new entrants into a sector that is increasingly technologically advanced. Furthermore, it can potentially help address key challenges the built environment faces, especially at a societal and planetary level.

Our built environment sits at the tipping point of a global climate crisis and a need for responsible resource consumption, all against a backdrop of ageing and often failing infrastructure. This rests alongside a case for change in building safety, asset reliability, improved whole-life costs, and improved construction productivity to name just a few current challenges.

To give a sense of how big and wicked these challenges are, the climate crisis has been described as a "hyperobject": a multifaceted concept that's too vast to grasp effectively. Hopefully this highlights a need for transformational change in our profession, and the reality is we have a short window to make change of this scale happen and make it stick long term.

So, what are we going to do about it? In *The Matrix*, lead character Neo was given the option of taking a red pill, which would enable him to understand what was occurring outside the illusion created by the Matrix, or a blue pill, which would allow him to return to experiencing only that illusion. Hopefully you choose red! We need to choose a future pathway which moves us out of the reassuring comfort zone of being slightly more efficient to a more radical technology-enabled future of a reimagined and thriving built environment.

We have already seen the value of information management using Building Information Modelling (BIM) and collaborative data sharing in our sector. In the coming years these processes and technologies will increasingly combine with communication networks, internet of things (providing sensors and other information) to enable Digital Twinning.

All these constructs offer real value to construction, however when we dial in Artificial Intelligence (AI) the potential impact multiples significantly, helping us unlock the true value of construction data which is often trapped or unstructured, to provide insights, optimise, predict, and potentially automate the decision-making process.

AI and its large language models are not new concepts (they have been in our lexicon since the 1950s), however unlike other technologies the big difference is the pace at which AI is moving, and this trajectory is unlikely to slow down. Indeed, AI has surpassed humans at a number of specific tasks already and the rate at which humans are being exceeded at new tasks is increasing every day.

Forms of AI are now prevalent in all walks of life and business, and the construction industry is in the age of AI, whether we recognise it or not. Indeed, the likelihood is that you are already using an AI-supported app such as ChatGPT, DALL.E or more complex algorithm-based generative design software. The availability of such technologies and their use cases will only increase and at speed. AI has the potential to revolutionise our sector, especially small and medium enterprises (SMEs),

by democratising access to emerging technologies and applications, enabling them to compete at a larger scale. With AI, SMEs can level the playing field, allowing them to tap into capabilities that were once only available to large construction organisations.

These concepts offer many use cases to our sector and indeed AI can immensely support project and construction management by analysing large volumes of project data across the value chain, spotting potential safety risks through computer vision, and offering insights for smarter decision-making. AI can also support the automation of repetitive tasks, such as everyday data entry, form filling, and report generation, all of which can dominate a construction manager's day. By automating these recurrent and time-consuming activities, teams can focus their efforts on more value-adding tasks, allowing them to make greater impact on project outcomes.

AI can also be used to analyse data ingested from various sources such as sensor networks, weather intelligence forecasts, as well as past historical data such as productivity outputs and project databases to predict potential risks and identify areas for improvement. The results of which can help project and construction managers make quicker, data-informed decisions and take proactive measures to safely maximise site activities. Essentially, AI is advancing how we work, making it smarter, faster and interacting better with our physical assets.

These technologies can also assist with surveying and monitoring to identify potential safety hazards, progress, quality issues and deviations from method statements or specifications. Project and construction managers are therefore empowered to take corrective action in real time, thus improving the safety, quality, and efficiency of the project.

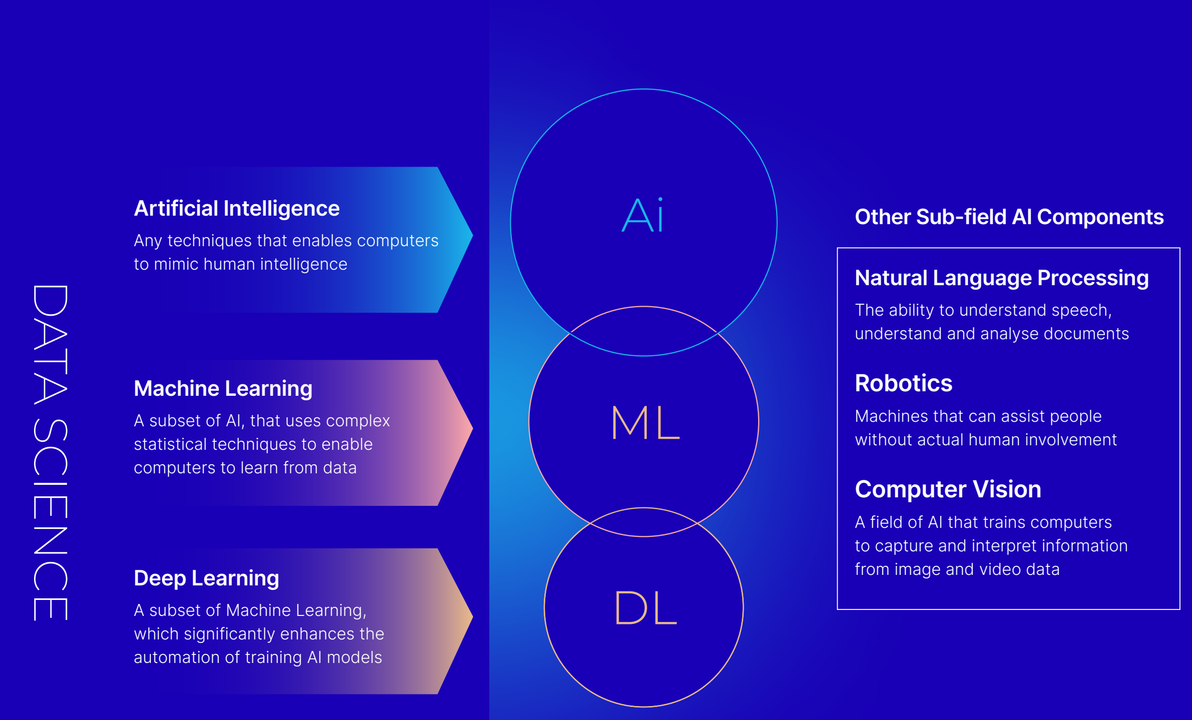
Conversely, some of the greatest use cases are downstream within the asset management world where asset availability and resilience are critical. A great example of that is bridge or dam monitoring solutions. AI and Machine Learning (ML) are used to process sensor data and automatically identify defects such as cracks or spalling and allow proactive maintenance regimes. We are going to see more of this type of application in operations and maintenance, from hospitals to rail, and other critical infrastructure. The great thing about these solutions is that they are helping to close the capacity and skills gap that exists today.

However, there will be a growing need for skill and capability development to mindfully harness AI and its benefits in an ethical and secure manner. Research has uncovered, for example, ethnic and gender biases in generative AI tools towards people in traditional trades, repeatedly failing to depict women or ethnic minorities working in the industry.

Therefore, we need to consider the AI black box problem. AI can do amazing things that humans can't, but in many cases, we have no idea how AI systems make their decision which we need to be mindful of. Essentially, we need a white box approach, offering transparency – understanding of the AI model decision making, reasoning and probability behind each decision as key considerations. There are various consent, data rights, and ethical data collection issues in relation to AI that need to be considered and resolved.

We also have the challenge of AI hallucinations to consider, where incorrect or misleading results are generated from AI models. These errors can be caused by a variety of factors, including insufficient training data, incorrect assumptions made by the model and biases in the data used to train the model.

Understanding AI in the context of our sector is vitally important to everyone involved in construction to help determine and shape how it might usher in new opportunities for your organisation and wider industry. This playbook sets out what AI and its sub-themes are, why it is important to construction, how to leverage it in your workflows, and the considerations you should take in your AI journey.



This playbook has been written by members of CIOB's Digital & Innovation Advisory Panel and aims to provide readers with a set of insights and practical applications to using AI in the workplace.

The purpose of the playbook is to help get industry started on a proportionate and well considered AI and data science journey. Firstly, understand your objectives and key challenges where AI can help. Treat AI as your new colleague, your construction assistant, potentially removing the burden from often repetitive data tasks. Work out where it can provide complementary analytical skills, pattern recognition, consistency, and increased processing speed.

AI gives us the opportunity to improve our everyday work and look to overcome many of the built environment's global challenges. Getting started should not be difficult, but it should however be mindful especially in terms of ethics and governance.

Each chapter is a stand-alone piece written by one of the expert members who sit on the Advisory Panel. We hope you find this document beneficial and welcome to the cusp of a new digital chapter.

David Philp FCIOB FICE FRICS FCInstCES FGBC
Chief Value Officer, Cohesive
Chair, CIOB Digital & Innovation Advisory Panel

Chapter 1:

Practical Implementation of AI in Construction

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Introduction

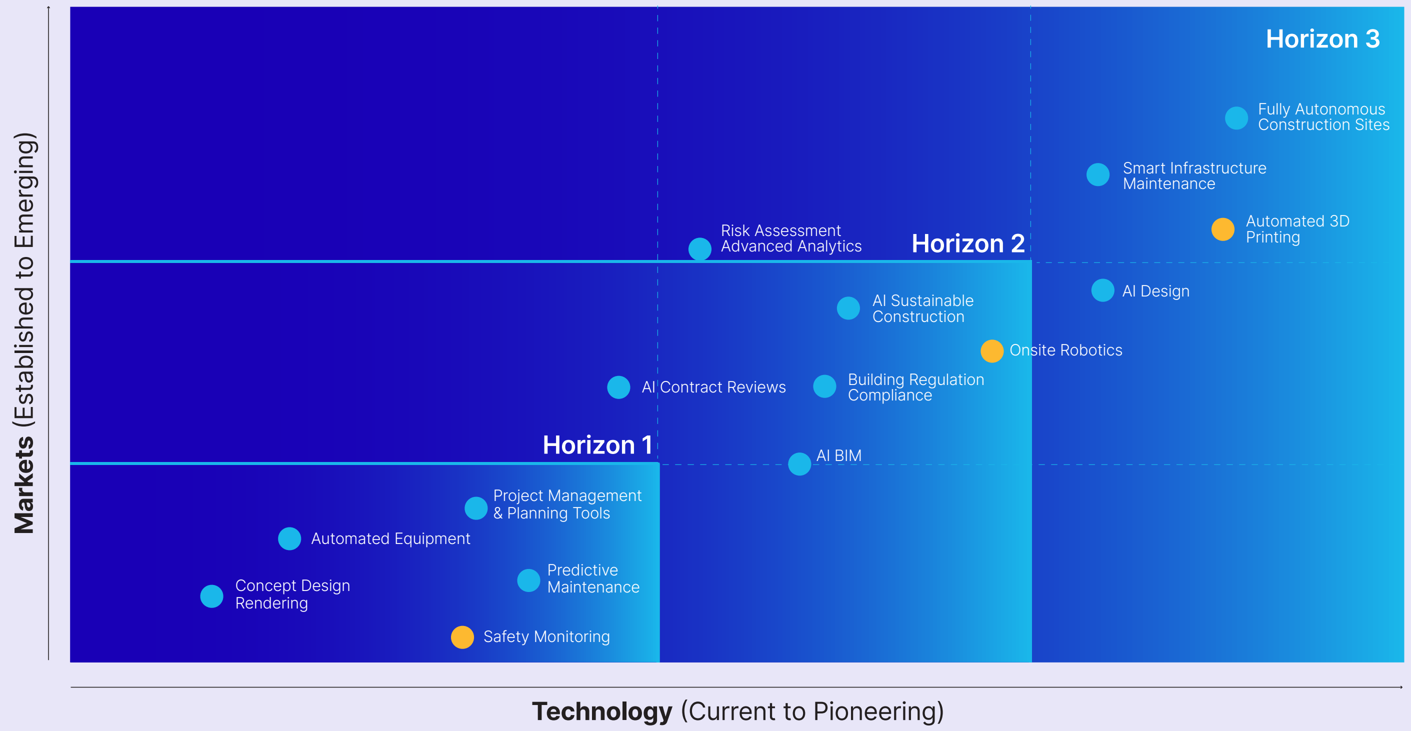
The construction industry faces increasing challenges due to the complexity of constantly evolving requirements. Most companies already understand managing the complexity of today's projects is only feasible with the adoption of digital processes and tools. The adoption of Building Information Modelling (BIM), for example, is mandated on publicly funded projects in the UK.

The popularisation of Artificial Intelligence (AI) through the release of new tools sparked both excitement and uncertainty. Perhaps due to that, the current implementation of AI in the construction industry has been restricted to punctual interventions throughout the lifecycle of a building – generative design, test fit applications, and project programme analysis.

Although the measured approaches seem to make sense in the early stages of the adoption of a new technology, how could AI uses be pushed further? What is needed to take these tools out of the box and start using them across multiple tasks? This chapter will cover these questions and explore what application categories already exist and what could be available in the future to support productivity, quality, and safety.

In Figure 1, the horizon map provides a framework for understanding the evolution of AI in the construction industry. The x-axis represents the maturity of the technology while the y-axis represents the market application, with each potential AI technology plotted accordingly. The map provides a visual of how AI technologies are currently being used, what is emerging and what the future could hold for the industry. However, it is important to note that due to the pace of change and breakthroughs in AI certain technologies could be accelerated and new applications created, therefore the map acts as a snapshot of our current understanding of AI applications and the predicted impact on the construction industry.

Figure 1: Horizon Map

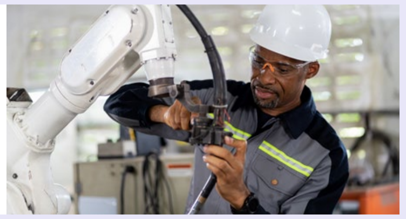


Safety Monitoring

AI-powered surveillance systems to monitor safety compliance

Onsite Robotics

Advanced robots for tasks like bricklaying or welding



Automated 3D Printing

AI optimising and controlling the 3D printing of buildings or large components

AI and our relationship with information

We are in an era where the way people interact with information has been drastically transformed. Gone are the days of consulting the Encyclopaedia Britannica; a simple search engine query now yields millions of results instantly. The rapid access to vast amounts of information on any topic is unprecedented, and AI is set to change this further.

Large language models can scan extensive content on a topic, providing summaries of the most common results and patterns. This capability could render lengthy searches obsolete, offering quick access to pertinent information.

This can be especially useful when searching for specialist topics, as it is often the case in the construction industry.

Do you need to know the width of a fire escape route? No problem, AI can find you this information.

Do you need to know how many power outlets a standard recommends are installed in a specific space? You can have this information in a matter of seconds. No need to scroll through hundreds of PDF pages.

This power can be your company's reality. Information recorded in archives can be connected to language models and unlocked. All the data collected from previous projects, successful or unsuccessful, can be accessed and used to inform our present and future decisions.

When looking into these opportunities we should remember AI is just a tool. As such, it cannot grasp the meaning of its outputs. AI models essentially establish associations between terms in their training data, relying on statistics to formulate expressions that humans can understand. From this, we can infer the outputs will only be as good as the inputs we can provide. The potential of AI can be unlocked with good prompts and structured data.

Digital skills

Professionals in the realm of digital construction are well aware tools alone are insufficient to produce deep changes in the construction industry. True transformation requires an understanding and mastery of these tools. To begin effectively integrating AI into daily operations, people will need a new set of delegation skills. Working with AI is similar to welcoming a new team member who requires an introduction to specific tasks. While initially time-consuming, investing time in training a new colleague proves beneficial in the long run, as it facilitates workload sharing.

Until we achieve the development of general-purpose AI, it is crucial to articulate the context and specifics of the tasks we assign to our current AI tools. If the task pertains to the construction industry, or a specific discipline such as architecture or engineering, this detail is imperative. Setting clear objectives is vital.

Crafting a clear and precise objective along with its context is a demanding task. There is significant value in defining the parameters within which the AI will function. Hence, terms like "prompt engineering" and "AI personas" are gaining prominence.

In the early phases of AI implementation, the technology performs best when tasked with activities we are already proficient in. Therefore, begin AI implementation with familiar tasks. This approach helps build incremental trust in the AI system among users.

Moreover, to obtain reliable results, it is essential to evaluate and validate the AI's output. This can be effectively done with tasks you are familiar with, as you possess the ability to discern between satisfactory and unsatisfactory results. Such validation processes are also pivotal in training and refining the AI.

AI models excel in speed, accuracy, and consistency as they do not suffer from fatigue or distraction. However, they lack the common sense needed for ethical and moral judgments. Initially, AI perform better in straightforward tasks.

AI is particularly adept at automating repetitive, rule-based tasks that have clear boundaries, such as data processing, basic data entry, and routine calculations. Nevertheless, AI models often falter in fully grasping the context and subtleties of human language and scenarios, lacking the common-sense reasoning that humans have.

While understanding and interpreting the nuances of complex tasks remains challenging for AI, its proficiency in straightforward tasks leads to enhanced accuracy and consistency in functions like data validation or quality control. By allocating these tasks to AI, organisations can optimise resource distribution, allowing human employees to concentrate on roles that demand critical thinking, creativity, empathy, and nuanced decision-making areas where AI typically underperforms.

The initial excitement and promise shown by AI tools such as ChatGPT might lead to inflated expectations about what can be achieved with these technologies. However, the reality remains that, in its current state and with its existing capabilities, AI is still a tool that necessitates specific user skills for effective utilisation.

AI and its categories

With AI applications multiplying every day, it is difficult to keep pace and understand the wider picture of where technology is going. However, understanding the boundaries within which these applications operate – their potential and their limitations – is fundamental to implementing tools that will deliver higher value for your company. This will allow for the right tool to be used for the right task. Moreover, the systems developed to carry on specific processes could potentially be reused on tasks of a similar nature.

Most applications currently developed for the construction industry fall within a few use categories. Let’s explore the main ones.

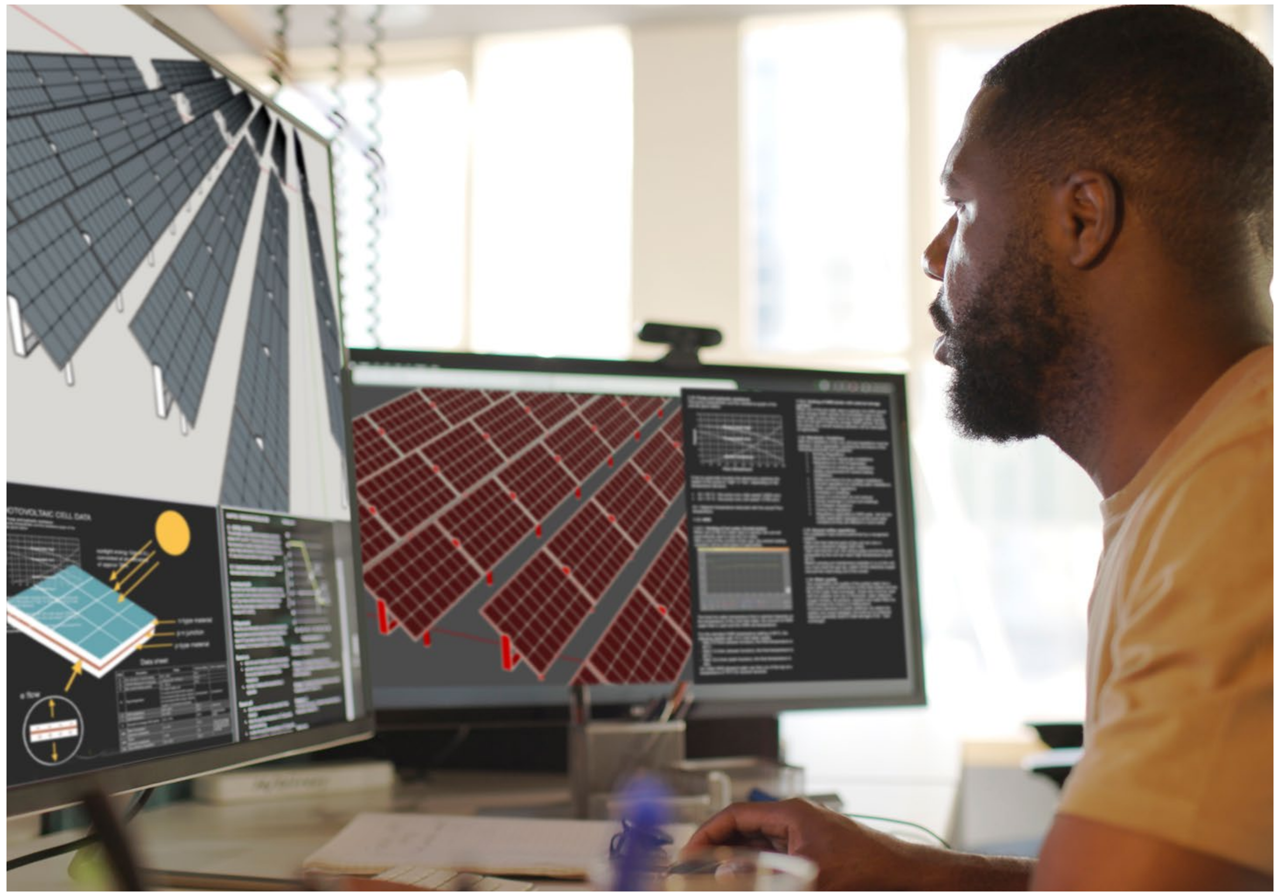
Analytics

Data analytics in AI encompasses the processing and interpretation of large and complex datasets by artificial intelligence. It involves using AI to uncover patterns, insights, and correlations within data that might not be immediately apparent to human analysts.

AI's role in data analytics within the construction industry is rapidly expanding, fundamentally changing how data is processed and utilised. AI's expanding capabilities enable the analysis of diverse data forms, including textual documents and video footage. A notable application is in scrutinising CCTV footage for safety violations, crucial for upholding health and safety standards.

Despite the vast amount of data generated in construction, companies often lack systems and resources for the storage and review of data. AI addresses this by organising and analysing data from various sources, thus uncovering causal relationships among project aspects like design requests for information (RFIs), schedules, and accident logs. These insights are invaluable for creating safer construction methodologies and providing proactive warnings to site personnel.

AI will continue to evolve, transcending the limitations of human cognition and conventional hardware. The shift towards General AI, with its capability of spanning different fields of knowledge, will redefine the boundaries of understanding and analysis. In this future, AI will operate beyond the constraints of human waking



hours and the finite processing power of our brains, initiating a new era of continuous and exponentially growing intelligence.

This evolution will not only transform how we process and interpret data in industries like construction but will also fundamentally alter our approach to knowledge and information. Where the use of the internet completed the "democratisation of information" the advancements of AI could lead to the concept of the "democratisation of understanding" - a future where insights and complex analyses are no longer the exclusive domain of experts. Instead, AI-driven analytics will make intricate patterns and sophisticated interpretations accessible to all, effectively levelling the playing field in terms of knowledge and decision-making.

Generation

Generation in AI refers to the creation of information, designs, or data by AI models. It involves using AI to produce new content or ideas based on given inputs, harnessing its ability to rapidly process and combine information in innovative ways.

In the evolving landscape of construction, AI is revolutionising content generation, offering solutions that far surpass human capabilities in speed and efficiency. This revolution is not just about pace; it is about the quality and innovation in outcomes.

Machine-generated content, for example, represents an opportunity, with parametric design at the forefront. Parametric design is a transformative approach where machines are fed specific inputs to test and generate design options. This method leverages AI's capability to prototype digitally, processing numerous possibilities to identify the most suitable design.

Another AI breakthrough in construction is image generation. Architects worldwide are experimenting with AI tools to develop concept renders. By inputting simple text descriptions, AI can produce conceptual visualisations in seconds, streamlining the design process remarkably.

As AI models become more sophisticated, the complexity of prompts they can interpret will also increase.

Building regulations currently present a challenge for AI applications. The potential for AI to understand and integrate regulatory requirements into design processes is immense. Designers could produce general arrangements and elevations of structures that adhere to building codes, through simple prompts.

The prospect of AI models gaining a deeper understanding of the numerous variables of construction, including client preferences, regulations, budget constraints, and construction methodologies, is groundbreaking. As AI continues to evolve, it could lead to the conception of buildings that harmonise these often-conflicting criteria, paving the way for design solutions previously unimagined.

Automation

Automation in AI is the use of artificial intelligence to perform tasks without human intervention. This involves programming AI systems to self-manage tasks, often in complex or dynamic environments, enhancing efficiency and reducing the need for manual input.

While industries like retail and hospitality are advancing with technologies like self-flying drones and robotic waiters, construction faces distinct challenges in adopting such automation. Construction environments are dynamic and unpredictable, unlike the controlled settings of manufacturing. This requires robots to adapt to different tasks and conditions daily. This complexity has slowed the widespread adoption of technologies such as bricklaying robots in construction.

Yet, as AI models evolve, their capacity to navigate complex environments improves. Drawing parallels with advancements in autonomous vehicles, AI-driven robotics in construction are becoming more adept, potentially allowing for their deployment in high-risk tasks, like confined space inspections.

Already, driverless technology is making headway in the industry, particularly in large-scale operations. The use of driverless plants in earthworks demonstrates the potential for AI to enhance precision and efficiency in construction tasks. These machines, utilising GPS and design data, are capable of executing specific tasks, such as piling, with remarkable accuracy.

> The prospect of AI models gaining a deeper understanding of the numerous variables of construction, including client preferences, regulations, budget constraints, and construction methodologies, is groundbreaking. As AI continues to evolve, it could lead to the conception of buildings that harmonise these often-conflicting criteria, paving the way for design solutions previously unimagined.

As AI and robotics blend more profoundly into the construction industry, they promise not only efficiency and safety, but also a shift in how we build our world, making it more sustainable, precise and with minimal impact on the neighbouring areas.

This silent revolution in construction, spearheaded by AI, has the potential to lead to a new age of innovation and environmental consciousness, reshaping the industry into a truly "invisible industry".

Case Study: **Automated Tender Management Solution Using Xefr and ChatGPT**

A prominent consultancy handling numerous public sector tenders approached Xerini to streamline and enhance their tender processing. They needed a solution to eliminate repetitive work and automate the evaluation process. Leveraging Xerini's flagship product Xefr, integrated with ChatGPT, the consultancy achieved significant productivity gains and reduced tender processing time.

The consultancy had several challenges they wanted to address:

- **Time-Consuming Tender Processing:** Evaluating public sector tenders was taking excessive time, involving repetitive and labour-intensive tasks.
- **Fragmented Tender Data:** Relevant data was dispersed across multiple documents and systems, making it hard to assess each tender's suitability quickly.
- **Manual Scoring and Filtering:** The existing bid/no-bid criteria were applied manually, leading to inconsistencies and inefficiencies.
- **Complex Question Extraction:** Large tender documents contained various questions, each needing individual answers.

An automated solution was implemented using Xefr, integrated with ChatGPT, to help streamline the entire tender processing workflow. This resulted in increased efficiency for tender processing, improved productivity by automatic repetitive tasks, and enhanced accuracy through automated bid/no-bid filtering.

Conclusion

In conclusion, the integration of AI into the construction industry represents a transformative era enhancing human capabilities rather than replacing them. Effective employment of AI requires a certain level of user skill and understanding. As we navigate this technological landscape, roles will evolve – transitioning from operators to supervisors, where professionals will increasingly find themselves checking and validating AI's work.

In the construction industry, the impact of AI will be profound, particularly on labour-intensive processes. AI can offer rapid, data-driven insights that would otherwise take weeks or months to compile. This shift promises not only efficiency but also a potential increase in accuracy and depth of analysis, driving better decision-making in the industry.

However, the full potential of AI hinges on the availability and structure of data. AI systems thrive on structured, well-organised data. The more precise and well-curated this data is, the more effectively AI can analyse, learn from, and make predictions based on it. This underscores the importance of rigorous data management and governance within the industry, as the quality of AI's output is directly influenced by the quality of its input.

In summary, AI in the construction industry represents a dual challenge and opportunity. While it demands new skills and roles, it also offers the potential to radically enhance efficiency, accuracy, and innovation. The journey towards harnessing the full potential of AI will be a collaborative one, requiring concerted efforts in skill development, role adaptation, and data management.

Chapter 2:

The Fundamentals of Artificial Intelligence

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Introduction

In this chapter, we embark on a journey to understand the fundamentals of Artificial Intelligence (AI) and Machine Learning (ML). These concepts, once the realm of science fiction, have now become pivotal in shaping the future of various sectors, with construction being no exception.

We will explore various facets of ML and AI, including different types of ML, classic models, neural networks, and the cutting-edge Transformer model, which includes technologies like GPT (Generative Pretrained Transformer). This exploration aims to demystify these sophisticated technologies, making them accessible and understandable to those outside the traditional realms of computer science and engineering.

What is Artificial Intelligence and Machine Learning?

AI, at its core, is the broader concept of machines being able to carry out tasks in a way we would consider “smart”. It is a branch of computer science that endeavours to simulate human intelligence in machines.

ML, a subset of AI, is where the real magic happens. It is the process by which machines learn to make decisions or predictions based on data. ML involves feeding algorithms data and allowing the machine to learn more about the performed task to improve its performance or make more accurate predictions over time. It's akin to teaching a child through examples; the more examples you provide, the better the child understands and applies the concept.

A practical example of machine learning in action is a spam filter. This program learns to identify and flag spam emails by analysing examples of both spam and regular emails, flagged by users. This process of learning is driven by a collection of examples or a 'training set'. Each example in this set is known as an 'instance'. Central to this process is the 'model', the part of the machine learning system that actively learns and makes predictions.

Why Use Machine Learning

The 21st century has witnessed an exponential increase in data generation, a trend that shows no signs of abating. This growing volume of data presents both a challenge and an opportunity: the challenge of processing and interpreting this data, and the opportunity to glean meaningful insights from it. ML offers a formidable tool in this regard, enabling the extraction of valuable information from large data sets.

One of the primary reasons for leveraging ML is its ability to process and make sense of this data, which is vital to successful outcomes from AI capability. It employs algorithms that learn from data, adaptively improving their performance as more data becomes available. This self-improvement is crucial; as the volume of data grows, so does the capability of the ML algorithms to derive insights.

Furthermore, ML shines in tackling problems that were either too complex or outright impossible to solve using conventional software development techniques. Consider the example of a spam filter — an application now ubiquitous in email services. Creating and maintaining a spam filter using traditional coding methods would require the formulation of an extensive set of complex, rigid rules ML, however, simplifies this task significantly. By learning from data, ML algorithms can effectively identify and filter spam, adapting to new types of spam over time without the need for constant human intervention in rule-setting.

As these algorithms are exposed to more data, they refine their models, enhancing accuracy and efficiency. This aspect is particularly beneficial in applications where the data environment is continuously changing or expanding.

Types of Machine Learning and Artificial Intelligence

In the realm of Machine Learning and Artificial Intelligence, the primary goal of these systems is encapsulated in two core objectives: classification and prediction. These objectives form the bedrock of the myriad applications of ML and AI, shaping the way data is analysed, interpreted, and utilised across diverse sectors.

Classification in machine learning refers to the task of categorising data into predefined classes or groups. For instance, consider the scenario of analysing customer reviews.

An AI system could classify these reviews as positive, negative, or neutral based on the sentiment expressed. This type of classification is not limited to single categories; a single data point, such as a photograph, could be classified simultaneously as featuring a cat and as a family portrait. The essence of classification lies in its ability to organise and interpret data in a meaningful and actionable manner.

In contrast, prediction focuses on forecasting or estimating an unknown value based on known parameters. A typical example is the prediction of property prices. An AI system could predict the value of a house by analysing various factors such as location, average income in the area, proximity to amenities, and historical price trends. The scope of prediction extends to generative AI, a burgeoning field where AI systems predict the next word in a text sequence or the answer to a query. This predictive capability is a cornerstone of modern AI applications, offering insights and foresight in a myriad of contexts.

Introduction to Classic Machine Learning Algorithms

In the world of machine learning, an array of 'classic' models exist, distinguished by their simplicity and efficiency, often operable on less advanced hardware without the need for high-end Graphic Processing Units (GPUs). These models form the backbone of many ML applications, particularly in domains where resources are limited, or rapid processing is paramount.

Linear Regression is one of the most fundamental and widely used statistical techniques in machine learning. It is a method used to model the relationship between a dependent variable and one or more independent variables. The aim is to find a linear relationship (a straight line or a plane, depending on the number of variables) that best fits the data. This model's simplicity and interpretability make it a go to choice for many predictive modelling tasks, such as estimating property prices based on various features like size, location, and age of the property.

Support Vector Machines (SVM) offer a more complex approach. SVMs are used for both classification and regression tasks but are more commonly used in classification problems. In these models, data points are plotted in a multi-dimensional space, and the SVM algorithm seeks to find a hyperplane that best divides the classes of data. One of the key features of SVMs is their ability to handle non-linear data using what's called the kernel trick, allowing them to be highly effective in complex datasets.

Decision Trees and Random Forests are particularly intuitive. A decision tree is a flowchart-like structure, where each internal node represents a test on an attribute, each branch represents the outcome of the test, and each leaf node represents a class label. They are simple to understand and interpret, but they can suffer from overfitting. Random Forests, an ensemble of decision trees, address this issue by building multiple trees and merging them together to get a more accurate and stable prediction.

Unsupervised methods like K-means clustering represent a different paradigm in ML, focusing on identifying patterns in data without pre-existing labels. K-means aims to partition the dataset into K distinct groups based on feature similarities. This method is particularly useful in scenarios where the data lacks explicit categories but still needs to be organised or segmented, such as grouping construction materials based on properties like durability, cost, and suitability for different environmental conditions.

Each of these classic ML models offers unique strengths and limitations, making them suitable for different tasks. Their relative simplicity and lower computational requirements compared to more advanced neural network models can often make them more accessible and practical in many real-world applications.

Introduction to Neural Networks and Deep Learning

In the arena of artificial intelligence, the neural networks use nature as the inspiration. Similar to the way birds inspired the creation of aircraft, to how plant burrs led to the invention of Velcro. In a similar vein, the workings of the human brain have spurred the development of Artificial Neural Networks (ANNs), a cornerstone of modern computational intelligence.

Artificial neural networks, as their name suggests, are a form of computing model designed to mimic the neural structure of the human brain. However, much like how aeroplanes do not replicate the flapping of birds' wings, ANNs do not exactly replicate the workings of their biological counterparts. They are, instead, a simplified and abstracted version, tailored to solve complex computational problems.

A fundamental building block in the architecture of neural networks is the perceptron, introduced by Frank Rosenblatt in 1957. The perceptron is a simple yet powerful model, where inputs (represented as numbers) are processed through a series of weights (akin to the synaptic strengths in biological neurons) and summed up. This sum is then passed through a step function to produce the output. Despite its simplicity, the perceptron was a significant step in the development of neural networks, paving the way for more complex architectures.

How do Neural Networks Learn?

The training of a neural network involves a process of fine-tuning, ensuring the network not only absorbs information but also applies it accurately to make decisions or predictions.

At the heart of this training process is the loss function. This function is a crucial component, serving as a guide to the accuracy of the neural network's predictions. In simpler terms, the loss function measures how far off the network's predictions are from the actual outcomes or the truth. The goal of the training process is to minimise this error, thereby improving the accuracy of the network.

Once the error is identified through the loss function, the network undergoes a process known as backpropagation. In backpropagation, the information about the error is sent back through the network. This feedback is crucial as it informs each part of the network about how much they contributed to the error and how they need to adjust to improve the prediction.

The adjustments mentioned are made to the weights, which are parameters within the network that determine the strength of the influence one node (a basic unit in a neural network) has on another. Initially, these weights are set randomly. Through backpropagation, the network algorithmically adjusts the weights to reduce the error, iteratively improving the network's performance.

This process of forward prediction and backward error correction continues until the network reaches a satisfactory level of accuracy, or until a predetermined number of iterations are completed. The end result is a neural network that has 'learned' from its mistakes, fine-tuning its weights to better predict or classify data based on the input it receives.

Deep Neural Networks

Deep Neural Networks (DNNs) represent a more intricate and powerful evolution of the basic artificial neural networks. These networks are termed “deep” due to their composition of multiple layers between the input and output, allowing them to model complex patterns and relationships in data. Each layer in a deep neural network transforms the input data to a more abstract and composite form, enabling the network to learn and make predictions or decisions with a high level of sophistication.

Within deep learning, there are specific types of deep neural networks designed for particular tasks:

Recurrent Neural Networks (RNNs): These networks are distinguished by their ability to process sequences of inputs by maintaining a form of 'memory' about previous inputs. This makes RNNs particularly well-suited for tasks involving sequential data, such as language processing, where the context and order of words are crucial. RNNs are used in applications like language translation, speech recognition, and text generation.

Convolutional Neural Networks (CNNs): CNNs are particularly adept at processing grid-like data, such as images. They use a mathematical operation called convolution which allows the network to focus on small regions of the input data, extracting features like edges, textures, and shapes. This makes CNNs highly effective for tasks like image and video recognition, image classification, and facial recognition.

Each of these networks has its architecture and method of operation, tailored to efficiently handle the specific nature of the data and tasks they are designed for. For instance, RNNs use their internal state (memory) to process variable length sequences of inputs, whereas CNNs use their convolutional layers to hierarchically extract features from fixed-size inputs like images.

Introduction to Natural Language Processing, Embeddings, Transformers and Large Language Models

Natural Language Processing (NLP) is concerned with how to program computers to process and analyse large amounts of natural language data, enabling them to understand, interpret, and respond to human language in a valuable way.

One of the pivotal components of NLP is the concept of 'embeddings'. In essence, embeddings are a sophisticated method of representing words and phrases in a manner that computers can process. They capture a wealth of information about words, including their meaning, context, and relationships with other words. By converting words into these numerical vectors, embeddings provide a bridge between the human use of language and the language of computers. Essential for developing advanced NLP applications such as sentiment analysis, language translation, and content recommendation systems.

Embeddings are the cornerstone for constructing ANNs that work with text. In the context of NLP, these neural networks are trained using embeddings, enabling them to 'understand' the nuances of language and perform tasks like text classification, summarisation, and question-answering.

A significant advancement in NLP has been the development of the Transformer model. This model uses a mechanism called 'attention' to weigh the significance of different words in a sentence. It has remarkable abilities in generating human-like text, understanding context, and even creating content that is indistinguishable from that written by humans. The Transformer architecture has become a backbone for various Large Language Models (LLMs), which are trained on vast datasets and can perform a wide array of language tasks with high accuracy.

The model works on two crucial learnings: first, the contextual relationships between words (how the meaning of a word can change depending on the other words around it), and second, a vast amount of general knowledge about the world.

The outcome of this extensive pre-training is a model that has a deep understanding of language and can perform a variety of language tasks. However, for specific applications, the model usually undergoes a second phase called fine-tuning. In this phase, the pre-trained model is trained again, but this time on a smaller, task-specific dataset. This allows the model to adjust its vast general knowledge to the specifics of the task at hand, whether it's answering questions, summarising text, or any other NLP task.

Conclusion

In this introductory chapter we have provided an overview of the fundamental landscape of Artificial Intelligence and Machine Learning. By understanding what AI and ML entail, their historical evolution, and the essential types and models, readers can appreciate the transformative potential these technologies hold. From classic machine learning algorithms to advanced neural networks and cutting-edge models like Transformers, AI's capacity to revolutionise industries, including construction, is evident.

Machine learning's ability to process vast datasets and make precise predictions offers solutions to previously insurmountable challenges. Neural networks and deep learning have brought us closer to creating systems that can mimic human intelligence and solve complex problems. Furthermore, advancements in Natural Language Processing and the development of models like GPT highlight AI's growing proficiency in understanding and generating human language, expanding its applicability.

As we move forward, the insights gained from this chapter will serve as a foundation for exploring how AI and ML can be practically applied to enhance efficiency, safety, and productivity within the construction industry. The journey from theoretical concepts to real-world applications continues to unfold, promising a future where AI-driven innovations are integral to industry advancements.

Chapter 3:

Machine Learning in Construction: Opportunities and Uses

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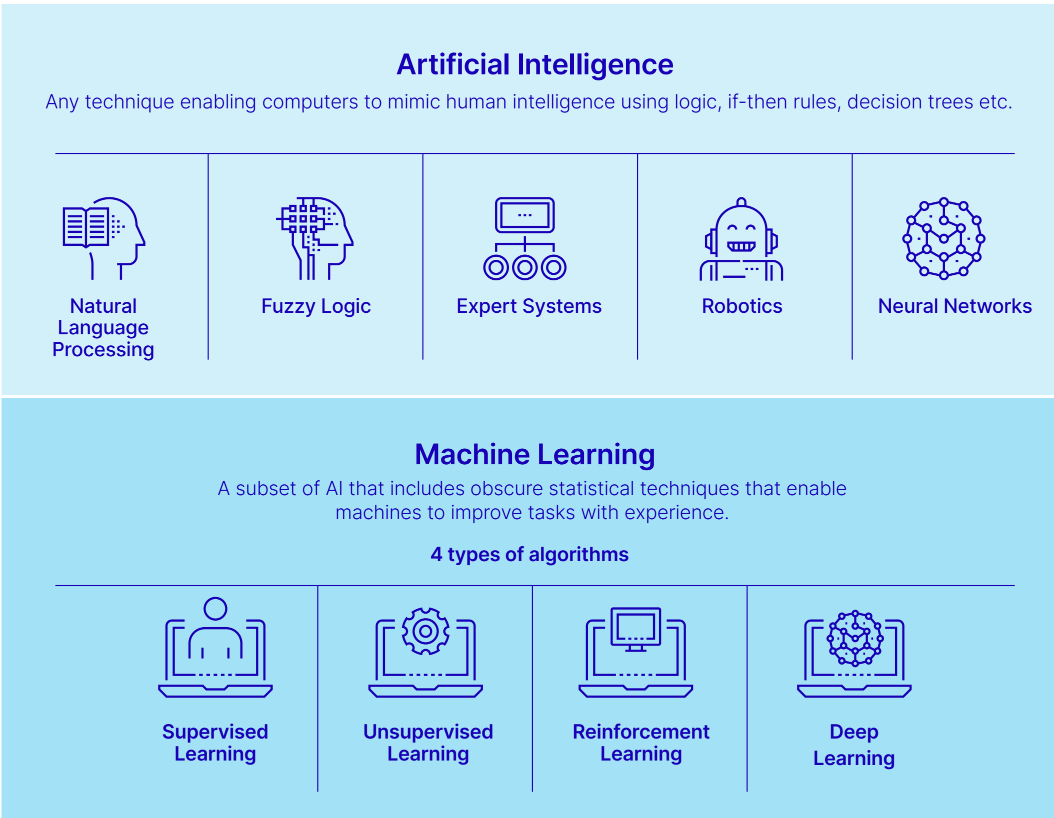
Introduction

Artificial Intelligence (AI) offers a plethora of opportunities in the built environment, revolutionising designing, constructing, operating, and reusing buildings and infrastructure. As per Figure 1, AI encompasses many facets including Natural Language Processing, Fuzzy Logic, Expert Systems, Robotics, Neural Networks and Machine Learning (ML). Which in turn allows a variety of opportunities to use and embed AI into our working lives.

Figure 1: Branches of AI and Machine Learning

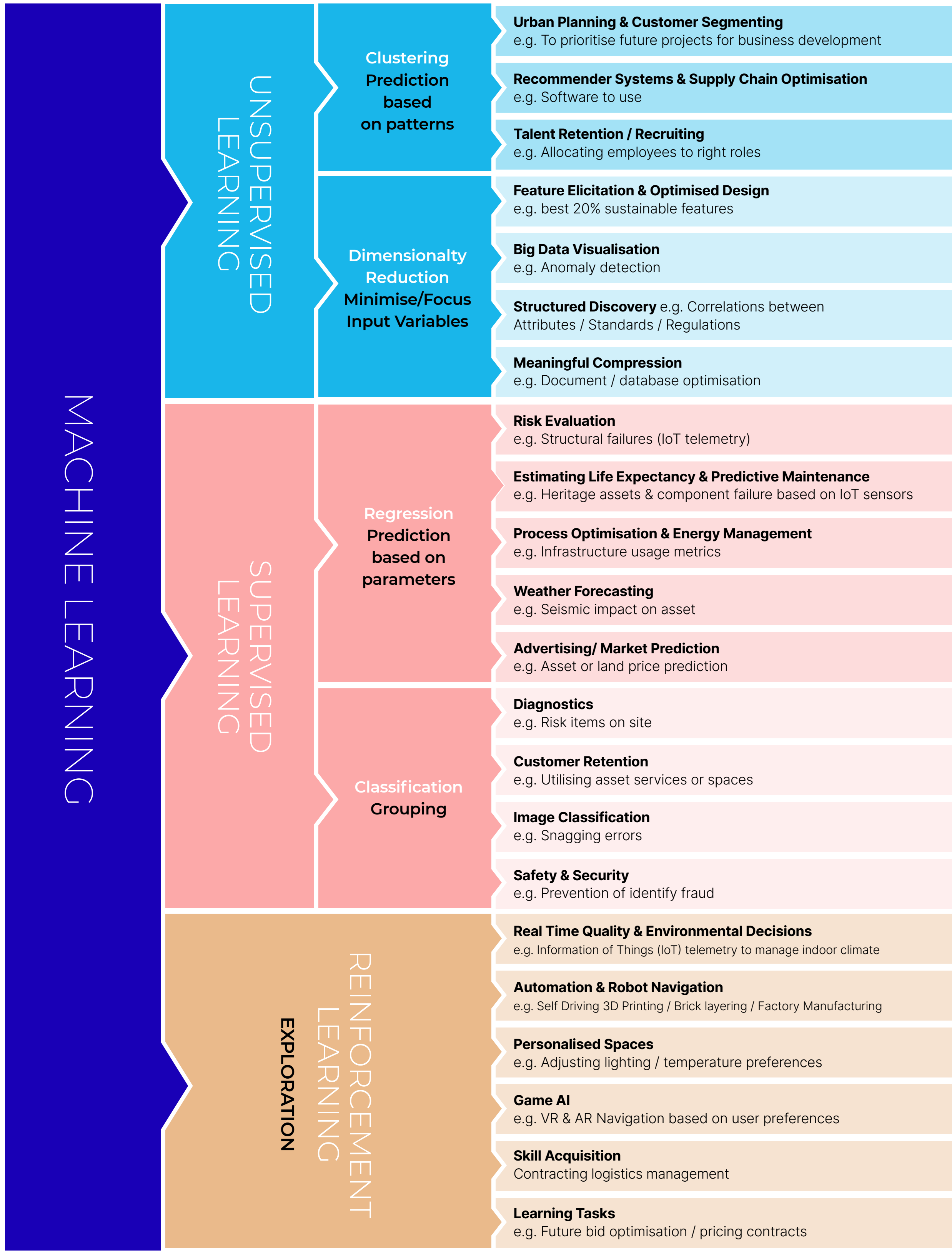


This chapter will focus on the possible custom key usages of different types of Machine Learning algorithms in construction, specifically Supervised, Unsupervised and Reinforcement Learning, in addition to off-the-shelf AI tools' usages and strategy to implement AI within an organisation.

Use Cases of Machine Learning Types

Figure 2 highlights the three branches of ML: supervised, unsupervised and reinforcement learning to help deliver a range of outputs for different uses in construction. A key benefit of ML is the ability to access its functionalities either through off-the-shelf tools or through bespoke applications created to fit the need of the business at different stages.

Figure 2: Uses of Machine Learning



Supervised Machine Learning

Supervised Learning (SL) is a branch of ML that relies on the machine/computer processer learning explicitly through large quantities of labelled training data - that has clear and defined outputs for its inputs, e.g. certain images all mean a specific object, which allows the machine to identify that object in its varied forms and formats. SL allows direct feedback and prediction of outcomes based on input data, which most often is structured data (Xu et al., 2021). SL helps resolve Classification and Regression problems as explained subsequently.

Classification

Classification algorithms use training data to detect, identify, recognise groups of objects or ideas, and hence predict the possibility that future data presented to it will fall into one of these predetermined categories (Sarker, 2021). Example use cases include:

- **Image Classification:** AI can be trained, using imagery data that has specific cognition outputs and meanings, to detect different types of issues in construction projects, e.g. finishing errors, incorrect installations of parts, erroneous lighting/pipe/duct fixtures, snagging errors on-site.
- **Diagnostics:** Data feeds can help train AI to diagnose issues during the lifecycle of an asset. For example, shortage of supplies and its effect on different building uses, anomalies in cost and time planning, and the effects of that on quality, analytical dashboards can be automated to help make appropriate decisions.
- **Safety and Security:** AI can be trained to identify fraudulent actions, people or objects. Examples include, detecting and filtering spam emails, unauthorised access codes, fake textual IDs, wrong face or fingerprint recognition, automated bots' communication, anomaly detection in processes, complicated phishing or cyber-attacks, dubious/risky physical actions on-site.
- **Customer Retention:** Data feeds providing explanation for different user behaviours can help AI detect user preferences for using different spaces, facilities, services and can help with asset operational and space management.

Regression

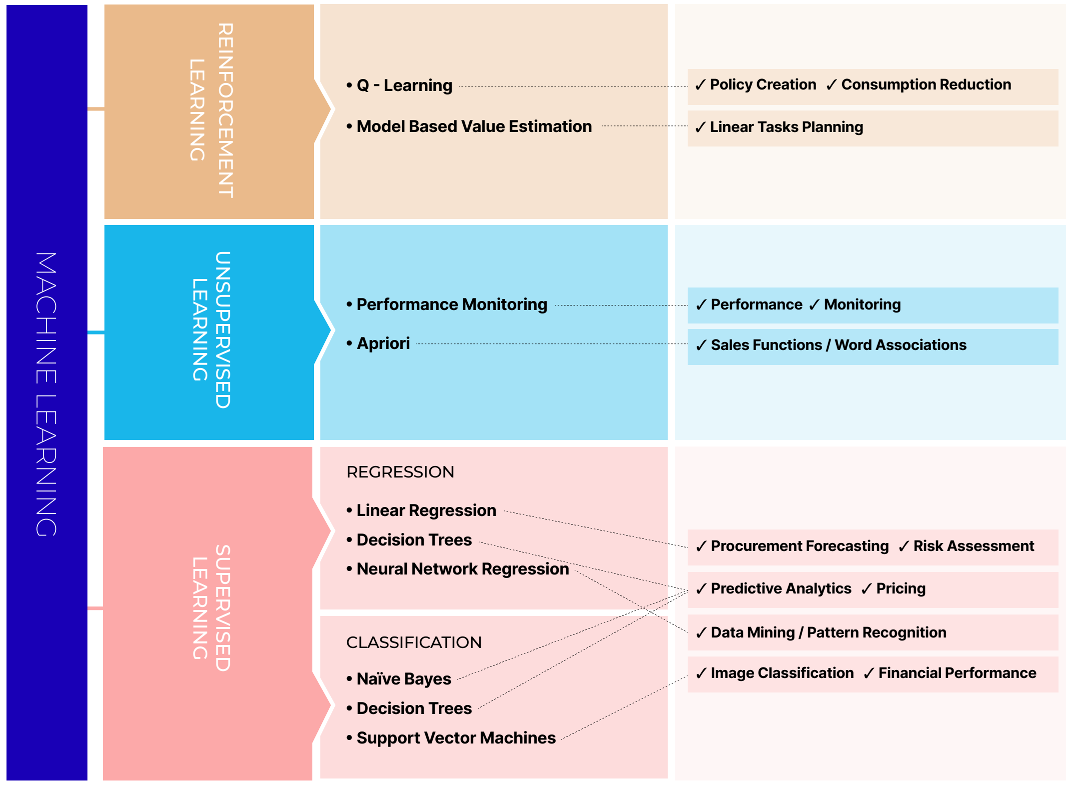
Regression algorithms use training data to investigate relationships between independent input variables and dependent results. It has the ability to predict continuous outcomes from future data (Sarker, 2021) Example use cases include:

- **Risk Evaluation:** Data feeds can train the AI to detect risks on site, in graphical models and in non-graphical documents and databases, e.g. images indicating potential risks on site missing clauses in documents, clashes or redundancies in information, non-aligning numbers or information in databases.
- **Estimating Life Expectancy and Predictive Maintenance:** Training data can help analyse future asset sensor telemetry Internet of Things (IoT) data to predict system/component failures based on their input performance data, e.g. valves, boilers, heating equipment. This allows proactive maintenance and reducing downtime and costs.
- **Process Optimisation and Energy Management:** AI can optimise asset energy performance by analysing spaces' legacy usage data, occupancy patterns, and energy prices to adjust heating, cooling, and lighting systems in real-time for maximum efficiency and users' preferences.
- **Weather Forecasting:** Using weather, seismic, flood data, AI can predict the need for adjusting construction materials, methods to counteract for natural hazards and disasters increasing asset resilience.
- **Advertising / Market Prediction:** Using variables e.g. market, land, construction, inflation, insurance prices, and market demand figures, AI can predict property prices, expected profits and suggest future investment planning.

Unsupervised Machine Learning

Unsupervised Learning (UL) relies on using large quantities of data to detect patterns, structures, and trends that can emerge from unlabelled training data. This is data that does not have clear outputs for its input feed and might be unstructured. Hence the evaluation or feedback could be qualitative or indirect with no specific conclusions (Naeem et al., 2023). UL helps resolve 'Clustering and Reduction' issues as explained subsequently.

Figure 3: Use Cases of Different Machine Learning Algorithms



Clustering

Clustering relies on dividing unlabelled data (with no specific identified outputs for the input data) into groups with similar characteristics, themes or data-points. Example use cases include:

- **Urban Planning and Customer Segmenting:** AI can analyse demographic data, traffic patterns, and environmental factors to inform urban planning decisions, such as the location of new infrastructure projects or the design of transportation networks.
- **Recommender Systems and Supply Chain Optimisation:** AI can analyse supply chain data to optimise use of construction materials, predict demand fluctuations and identify the most efficient methods and suppliers to minimise costs or delays.
- **Talent Retention and recruiting:** AI can detect skillsets from applicants' resumes, portfolios, interviews or tests and categorise them into clusters of suitable job placements.

Reduction

Reduction refers to reducing the number of features in datasets, to model the data, recognise its patterns, remove redundances, find meaningful data properties and focus its outputs. Example use cases include:

- **Big Data Visualisation:** AI can help reduce uncertainties and anomalies in unstructured large amounts of data to help extrapolate significant patterns, e.g. in continuous IoT sensor telemetry data from assets (energy, pollution, noise, etc.) to help manage spaces more efficiently.
- **Feature Elicitation and Optimisation Design:** AI can optimise asset designs for energy efficiency, structural integrity, and user comfort, which leads to more sustainable buildings, efficient resourcing while providing better living and working environments.
- **Structured Discovery:** AI reduction aids in identifying the relationships between the most significant attributes in unlabelled datasets, showing which can be controlled, or changed to affect others positively, e.g. relationship between changes in temperature and worker production levels.
- **Meaningful Compression:** AI can also be used to compress documents and database structures/information to remove redundancies or conflicts.

Reinforcement Machine Learning

Reinforcement Machine Learning (RML) relies on the machine/computer AI processer utilising large quantities of data testing to self-interpret positive and negative results based on “rewards” and “punishments”. This means the machine learns through trial and error (positive & negative reinforcement), that generates maximum rewards and enhances performance based on results of different data feeds (Sivamayil et al., 2023). Example use cases include:

- **Real-time Quality and Environmental Decisions:** AI testing can help optimise indoor climate quality, e.g. by changing heating and lighting parameters, AI can improve health and safety, humidity, air quality, while being sustainable and cost effective.
- **Automation and Robot Navigation:** AI can derive best methodologies to automate various construction tasks and enhance robotics performance, e.g. brick layering, 3D-printing, installation, modular production, concrete pouring.
- **User Behaviour via Game AI:** Using Virtual and Augmented Reality applications, AI can detect through change of user choices, routes or usages inside these applications, the best decisions to employ within an asset for management and maintenance.
- **Personalised Spaces:** AI-powered systems can monitor user behaviour to personalise building environments based on individual preferences, e.g. adjusting lighting, temperature or workspace layout to enhance productivity, comfort and well-being.
- **Skill Acquisition:** Through trial-and-error, AI can help acquire skillsets for management, design, logistics, procurement, etc.
- **Optimising Tasks:** Similar to the above, AI can create optimal bids, pricing, contracts, schedule planning, risk assessment, resources acquisition, etc.

Figure 4: ML Algorithms Uses and AI Tools for Different Uses in Each Lifecycle Stage

Use Cases of ML Algorithms and AI Tools per Lifecycle Phase

Figure 4 subsequently provides the following comparative perspectives:

- Analysis between the different off-the-shelf AI tools available in the market and their possible usages within each lifecycle stage of an asset.
- Analysis of which ML algorithms can be used to create bespoke solutions for different use cases within each lifecycle stage.

Lifecycle Stage	Example AI Tool	Usage	Type of Machine Learning	Case Uses of Machine Learning for each Lifecycle Stage	Example of Machine Learning Algorithm to assist in it	Type of Machine Learning
Planning	**ChatGPT** →	Information Content & Code Generation	All AI tools utilise Reinforcement Learning due to enhancing output based on feedback from text prompts	Life expectancy Estimation →	Life expectancy Estimation	Supervised
	Testfit →	Space Planning, Real Estate Feasibility		Environmental Impact Estimation →	Environmental Impact Estimation	
	Chat Mind →	Mind mapping, Brainstorming		Supply Chain Analysis →	Supply Chain Analysis	
	Calendar AI →	Calendar Scheduling		Budget / Financial Analysis →	Budget / Financial Analysis	
Design	**Finch 3D** →	Design Optimisation & Automation		Energy Forecasting →	Exponential Smoothing	Supervised
	Rytr →	Information Content & Code Generation		Design Optimisation →	SVR/SVM	
	Varys AI →	Interior Design Generation		Model Optimisation →	Gradient Descent	
	Veras →	Image Rendering		Design Classifications →	Logistic Regression	
	Midjourney →	Image Generation		Material Optimisation →	Neural Networks	
	DALL-E →	Image Generation		Sentiment Analysis →	Naïve Bayes	
	Sora →	Video Generation		Risk Analysis →	K-Means Clustering	
Construction	**PowerBI** →	Data Analytics & Visualisation Dashboards		Predict Embodied/Oper. Carbon →	Autoregressive NN	Unsupervised
	Co-Pilot →	Information Content & Code Generation		Sustainability Optimisation →	Decision trees	
	Kreo →	Takeoff and Cost Estimation		Waste Management →	Logistic Regression	
	CostChecker →	Manufacturing Costing		Process / Logistics Enhancement →	Cluster Behaviour	
	Ayanza →	Time Scheduling Management		Pricing / Bid Optimisation →	Discriminant Analysis	
	Notion →	Task and Time Assignment		Stakeholder Segmenting →	Logistic Regression	
	viAct →	Site Monitoring, Safety Assessment		Time Series Forecasting →	Support Vector Regression	
Operations	**OpenSpace.ai** →	Built Site Capture, Mapping, Management		Consumption Patterns CO2 →	Gaussian Mixture	Unsupervised
	Procore →	Document Control & Collaboration		Maintenance Diagnostics →	Hierarchical Clustering	
	Fieldwire →	Data Analytics & Visualisation		Operational Patterns →	Self Organising Maps	
	IBM WatsonX →	Natural Language Proc. & Data Analytics		Maintenance Segmenting →	K-Means Clustering	
	DroneDeploy →	Analysis of assets realtime data/imagery		Big Data Analysis →	Adoptive Resonance	
	ANEVA →	Performance optimisation of industrial ops		Outcome Association →	Association Rule	
	BrainBox AI →	Weather Forecast in Energy Optimisation		Carbon / Energy Efficiency →	Q and TD learning	Reinforcement
	Nantum →	Energy and Carbon Data Management		Indoor Environment Optimising →	Q Learning	
	Singu FM →	Facilities Data Management		Real-Time Telemetry data →	SARSA	
	Facilio →	Property Operations Platform		Sustainable Health & Safety →	Adoptive Learning Rate	
	ClickUp →	Maintenance Project Management		Resources Procurement →	Gradient Descent	
	Spaceti →	Space Management Platform		Robot Simulations →	Deep Q Networks	

A 12 Step Strategy to Implement AI within an Organisation

When embarking on the journey to overhaul an organisations workflows and procedures to include or use Artificial Intelligence within its strategic processes or individual projects, it is important to go through a thorough analysis of the business needs and create a plan for implementation as per the 12 steps below:

1. **Determine what can AI do – potential uses (based on types of AI)?**
2. **Perform a Gap Analysis – what do we need that AI can help with?**
3. **What skillsets are needed inhouse and outsourced (computer scientists / scripters / sustainable designers etc)?**
4. **What existing off-the-shelf solutions and tools can be used?**
5. **What uses need custom solutions?**
6. **What types of AI do we want to use?**
7. **What bespoke tasks and dashboards will be created for those bespoke uses?**
8. **What data is needed for them, what do we have, what's missing, how can that affect results, and what algorithms to use?**
9. **How can we assess deliverables quality/performance – Are there any KPIs?**
10. **What are their risks/legal implications, who is liable for them?**
11. **How often will the AI need to be updated?**
12. **How to integrate them with existing inhouse and supply chain systems?**

Conclusion

In summary, this chapter started by presenting various use cases of Machine Learning within the different lifecycle stages of a building. It then introduced practical examples for using either existing market AI tools or creating bespoke solutions using which types of ML algorithms, in addition to the generic strategy to implement AI within an organisation.

Chapter 4:

The Importance of Machine and Deep Learning

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Introduction

Artificial Intelligence (AI) has brought about significant advancements in various fields, with Natural Language Processing (NLP), Large Language Models (LLM) and Generative AI being at the forefront for those working in construction. These technologies have transformed the way we interact with existing technology and tools, but also changes our perception on how industries can operate. In this chapter we explore the importance of Machine and Deep learning and examine the intersection of these technologies and their applications in the construction sector.

Natural Language Processing (NLP), Large Language Models (LLM) and Generative AI

A Large Language Model (LLM) is a type of AI algorithm that uses deep learning techniques and massively large data sets to understand, summarise, generate and predict new content. The term generative AI also is closely connected with LLMs, which are, in fact, a type of generative AI that has been specifically architected to help generate text-based content. The recent genre of generative AI applications like ChatGPT, Google BARD and others are examples of LLM based generative AI.

AI Applications in the construction sector

There are various applications of AI emerging all the time. Historically, there have been several limitations and impediments which inhibited the development of full-scale, robust applications which the industry could adopt, until recently.

The major limitation was the lack of access to structured (or even unstructured) data and the lack of connectivity to provide data storage and exchange infrastructure ecosystem. Both these limitations have been largely addressed in the past few years with the advent of the internet, big data, and cloud computing.

In the context of the construction industry, a major development in this regard has been the almost ubiquitous adoption of Building Information Modelling (BIM) in design and construction. One view of BIM could be a large data store of all aspects of a facility. Like all areas which rely on large amounts of data, a mature BIM ecosystem promises to open various possibilities for the development of intelligent decision-making systems reliant on large datasets. A BIM ecosystem's impacts can be envisioned in Figure 1.

This vision now largely exists in practice and will rejuvenate the interest in these systems and indeed advanced AI systems fundamentally driven by data captured in BIM-based repositories (like the Common Data Environment) in many cases.

Figure 1: Potential impacts of a BIM Ecosystem

Intelligent Regulatory Compliance (i-ReC) – An example in AI-driven regulatory compliance in the built environment

Following the fire at Grenfell Tower, the well-publicised Independent Review of Building Regulations and Fire Safety, led by Dame Judith Hackitt, was published in 2018. The review examined high-rise residential building safety, fire regulations and related compliance and enforcements.

In order to avert similar disasters in the future, the report clearly recommends the building regulations and associated guidance, including the Approved Documents, need to be authored, applied and enforced in a fundamentally different way:

"[...] the current regulatory system for ensuring fire safety in high-rise and complex buildings is not fit for purpose."

The current method for identifying relevant standards is manual and time consuming, with no industry-wide programme that processes and automates changes to compliance, or standards.

Figure 2: Schematic overview of architecture of i-ReC, the envisioned platform strategy.

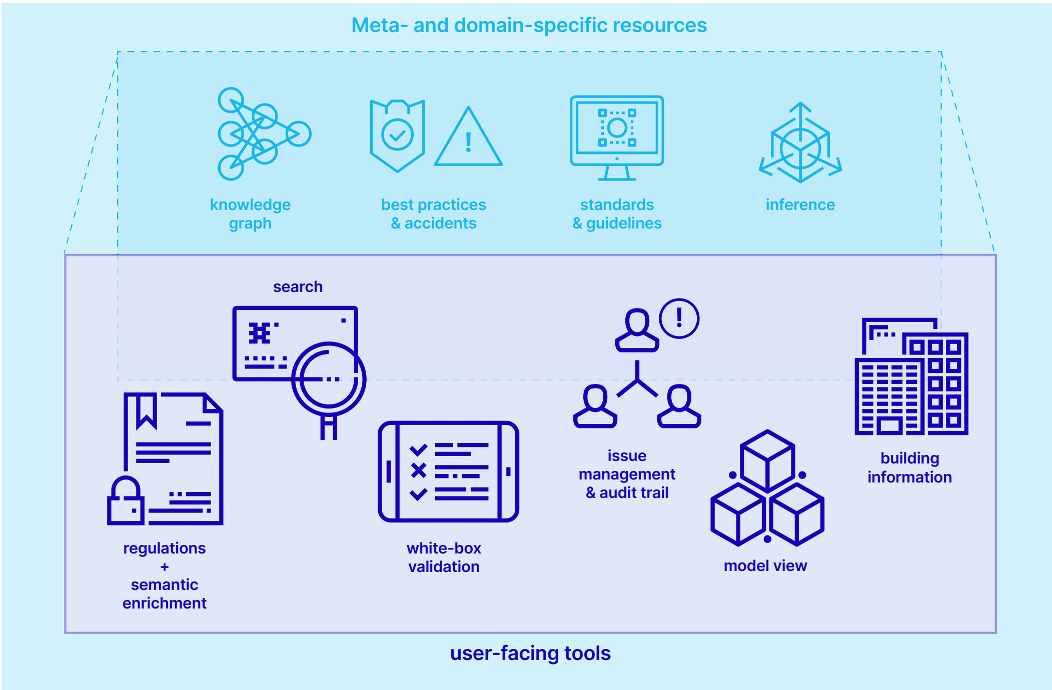
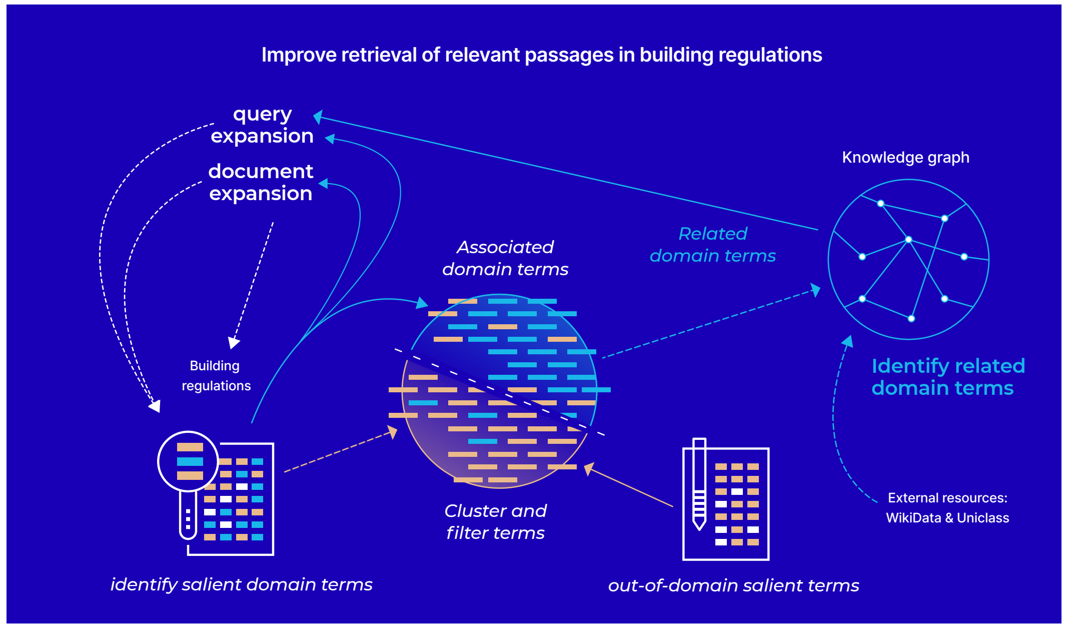


Figure 3: An outline of the Information Retrieval (IR) system for i-ReC



The aim of the i-ReC project was to develop an automated process of gathering and checking standards that would be easily searchable using a semantic search engine.

By developing a search engine and adding automation to this process, i-ReC would increase project efficiencies and reduce the risk of human error.

The i-ReC project is a collaboration between Northumbria, Strathclyde and Heriot-Watt University. Funding was provided by the Building Research Establishment on behalf of the Construction Innovation Hub. The team's approach was innovative to the industry, applying techniques of Natural Language Processing (NLP) alongside ML to reduce the manual effort of database maintenance.

Figure 2 shows a schematic overview of architecture of i-ReC, the envisioned platform strategy. Many user-facing tools would benefit from shared open standards and resources, e.g., datasets, shared vocabularies, guidelines, conversion algorithms and so on. In this paper we focus on NLP tools to process regulations, both from the perspective of meta- and domain-specific resources as well as the perspective of user-facing tools.

The Information Retrieval (IR) system as seen in Figure 3, enables search through the contents of building regulations. To improve the matching potential of the queries and passages we implement Document and Query Expansion, respectively. Candidate terms are computed relying on associations between salient terms that were identified in the regulatory texts, as well as using relations found in a Knowledge Graph that links to external domain knowledge.

i-ReC's integration with other BIM platforms retrieves all requirements for the entire model and provides a complete audit trail for all stakeholders. The i-ReC platforms other constituent parts are under development. i-ReC searches through around 420 regulatory and standards documents out of close to 800 such documents in the UK due to licensing restrictions. A detailed description of i-ReC is beyond the scope of this report, but more interested readers can refer to our resources section.

Summary

AI technologies will positively impact the construction industry, ushering in a new era of innovation and transforming traditional methodologies.

Tools like i-ReC exemplify how the industry can harness AI to ensure regulatory compliance in the built environment. The incorporation of AI in the construction sector is not merely a speculative future, but a present reality that is already bringing about significant changes. As these technologies continue to evolve, they will undoubtedly play a pivotal role in shaping the future landscape of the construction industry.

Chapter 5:

The Foundations of Quality Data

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Introduction

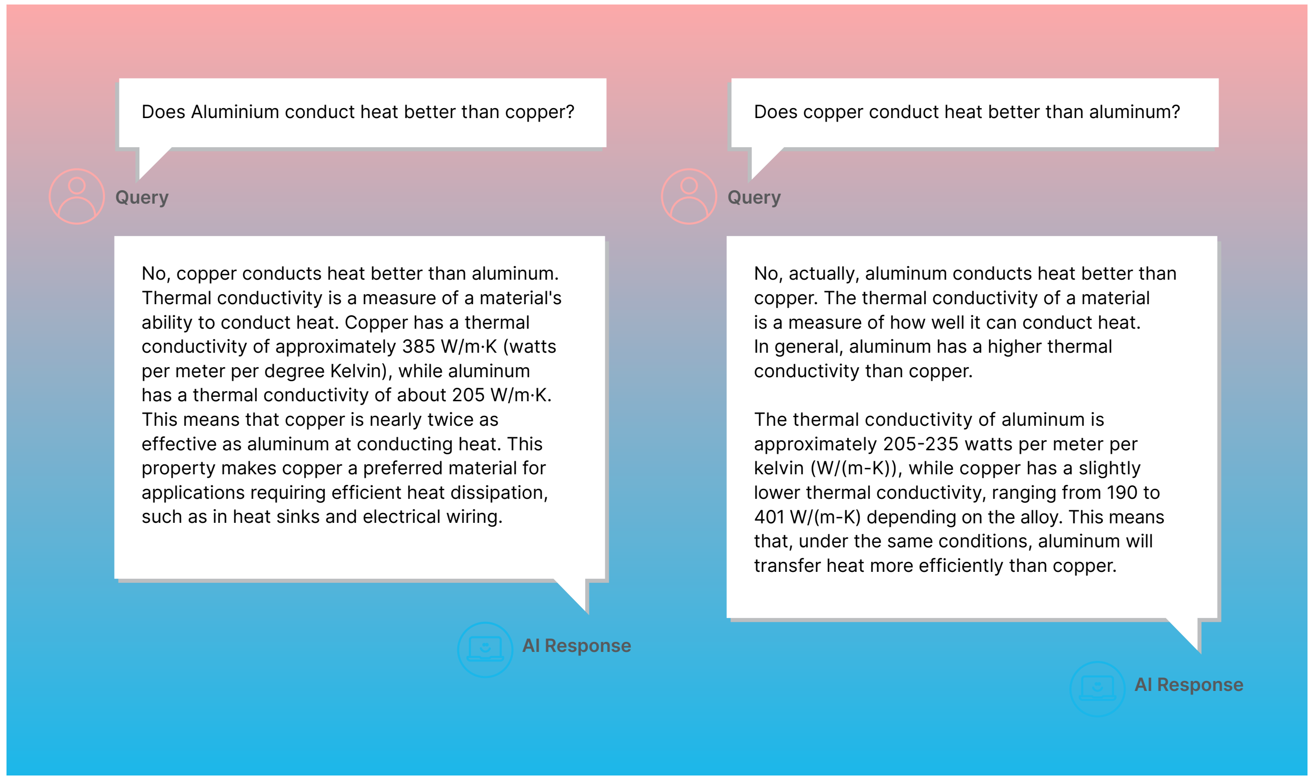
Quality data has always been at the foundation of good and accurate decision making, regardless of the process or technology in use. As we move further into the implementation of AI, we must appreciate the powerful role data plays in both its successes, and failures.

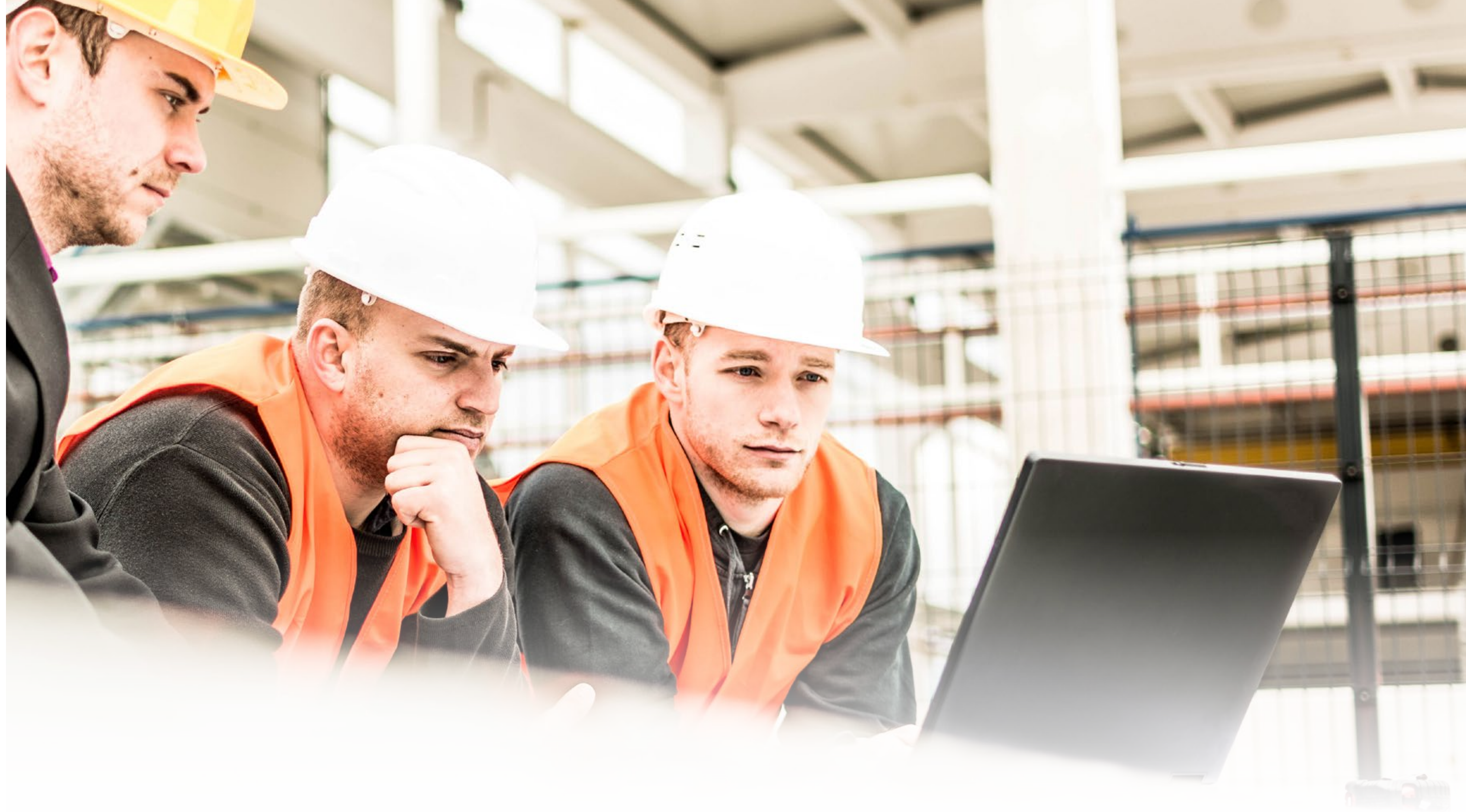
As the pathway to AI, machine learning uses algorithms to recognise patterns and learn insights from data. The more relevant, accessible, and complete your data is, the more likely machine learning is to forge good insights, and the more accurate your AI outputs will be. In short, the quality of data accessible to AI is what drives its performance, accuracy, and reliability. AI, just like humans, will only ever be as good as the data it has access to.

Data quality and LLMs

Recently there has been a huge influx in the use of applications powered by generative Large Language Models (LLMs) such as ChatGPT, Bard, and Llama, both for personal and professional use. The risks and opportunities of using this type of AI are covered elsewhere in this playbook, but it is important to cover the data quality and reliability of LLMs in this chapter. LLMs are trained on a vast amount of general text data such as websites, online blogs, and forums. Most generative LLMs also learn from user feedback and conversations on an ongoing basis.

LLMs are a case study in poor data leading to poor outputs, with vast examples online of LLMs providing incorrect or conflicting responses to relatively simple questions for example:





This type of generative AI often takes a huge dataset of largely unstructured, unverified, and sometimes conflicting information (the internet) and uses that to form a response to a query that it believes the user will be pleased with. If the user is happy with the response they receive, they might upvote it or respond positively and the AI will use that response to update its data set and determine how it will reply next time it is asked a similar question. The data being used and the process of updating it is not inherently objective, and therefore the intelligence is originally based on, and can be continually skewed by, human bias. The example on page 36 highlights this point as I ask the question with a British spelling of aluminium, but due to human bias in its data input, it returns the query with the American spelling.

One very clear lesson from our experience of applications powered by generative LLMs so far is that they are very good for certain tasks, but not so great at providing trustworthy responses to specific questions. Crafting well-designed instructions (prompts) for AI will certainly help generate more relevant responses, but ultimately the nature of the data available to these LLMs makes it impossible to completely trust the outputs.

> LLM chatbots, such as ChatGPT, should be considered with the same level of trust as a brand-new colleague who has offered to complete some work on your behalf. They may appear to know what they are talking about, but you would not submit their work without checking it first because you do not know their level of experience, expertise, and trustworthiness.

This is a critical lesson for organisations that wish to develop or procure AI tools either using their own data or data provided from other sources: if the data is not accurate, relevant, and trustworthy before it is used by AI, then how realistic is it to expect the AI outputs to be accurate, relevant, and trustworthy?

Data is widely considered to be one of the world's most valuable resources and therefore it is important to treat data with the same respect and care as you would treat any other valuable asset.

Although not always considered the most exciting piece of the technology puzzle, good data governance strategies are a critical part of any business case for AI. Robust and effective data governance will also have a profound knock-on effect across an organisation. If data is well organised and trustworthy, then businesses will be able to analyse that data with higher precision and clearer insight across the board.

The importance of quality data

The table below summarises some of the reasons why data quality is important:

BIM Use	Outcomes
Accuracy and reliability	AI models learn patterns and make predictions based on the data they are trained on. If the data is accurate and reliable, the model is more likely to produce accurate and reliable results. Poor-quality data can lead to incorrect conclusions and unreliable predictions.
Cost efficiency	Poor-quality data can lead to inaccurate predictions, which can result in costly errors and inefficiencies. Investing in high-quality data from the beginning can save resources in the long run by reducing the need for model retraining and correction of errors.
Generalisations	AI models are often designed to generalise patterns from training data to make new predictions and include those in future outputs. High-quality data ensures that the model learns relevant and representative patterns, allowing it to generalise well to new situations.
Bias mitigation	Biases present in training data can be learned and perpetuated by AI. Data taken from sources such as the internet (web scraping) are particularly susceptible to bias. Data should not be skewed toward specific groups or perspectives.
Ethics	Data must enable ethical and responsible AI systems, minimising the risk of unintended consequences and harmful outcomes.
Regulatory compliance	The data being used by AI must be stored, shared, maintained, and used in compliance with legal and regulatory requirements such as GDPR.

What does good quality data look like?

Ultimately the best data for AI will depend entirely on the type of model being used, and the tasks it will be asked to undertake. To prepare your data for use by AI there are some key considerations that must be made.

Amount of data needed

There is a common misconception that more equals better when it comes to data, but the bigger the dataset the more computer power is needed to tackle it. This has implications not only on affordability, but also on the environment, with larger AI models having more energy expenditure and therefore more carbon emissions.

So how small can you go? The minimum size of the dataset that is required for a successful AI application will depend on factors such as the complexity of the model you are trying to build, what activities you want it to carry out, and even the time frame that is at your disposal. The target should be to achieve the best results with the minimum number of resources. A sensible way to manage this is often by first trying simple models with few data points before trying more advanced methods that require more data.

Type

AI systems can work with data from diverse sources, in diverse formats, about diverse business processes.

Preparing and maintaining data

There are several steps that must be taken to prepare and maintain data used by an AI system:

1. **Identifying and sourcing relevant data** – There must be a clear understanding of the scope of the AI model, and therefore the data it will require to carry out the required tasks efficiently and accurately. Decisions must be made about where the data should come from, including considerations about the security of that data, implications to IP or GDPR if you are using personal or open-source information, and how and when the data will be updated.
2. **Annotation and classification** – Data such as text, images, or model objects should be annotated using metadata to make them recognisable to a computer. Machine learning can then comprehend the information and perform appropriate actions. There are many ways to automate these processes, but for projects using models or BIM this can be more accurately managed and maintained as the models are being produced and updated throughout a project lifecycle.
3. **Verification** – There should be a plan in place to test the validity of the data being used, its trustworthiness, and how its accuracy is maintained before, and during, its use. Initially a representative sample should be used to carry out tests with a minimum viable product so that resources are not wasted further down the line.
4. **Quality control** – A testing plan should be in place to periodically test the AI outputs for accuracy and to review the integrity of the data in use. This may include daily or annual checks, depending on the nature of the tasks being carried out by AI and the risks profile of the project.

An AI strategy must form part of an overall information management plan from the earliest possible stage of a project or build; you will find a template on creating an AI strategy in the resources section. Information Managers, BIM Managers, and data engineers in the built environment can help significantly in making data available and usable, collecting it and arranging it into a form that can be ultimately useful for AI. AI cannot find or do anything unless there is a good set of data to work from. By adding AI uses into your information management plan early you can avoid doubling up on work and cost.

Summary

Good quality data forms the foundation for building effective, reliable, and ethical AI systems. It influences the performance, capabilities, and societal impact of AI applications. Therefore, it is important to prioritise data quality in your AI initiatives to maximise the benefits and minimise potential risks.

Chapter 6:

AI, the Law and Contracts

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Introduction

The use of generative AI, as with all new technologies and process, results in new risks, potential misunderstandings and differing expectations, and therefore potential disputes. Whilst not stifling innovation, we therefore need to balance such innovation with mitigating risks and unintended liability.

The key areas of risk and dispute fall into a few categories:

1. **Copyright**
2. **Confidentiality**
3. **Reliance and Reliability of the AI results**
4. **Personal Data**
5. **Ethics and Bias**

Copyright

It is important to differentiate at this point between public AI models, and private or closed AI models. Private or closed ones would be those accessible only to those in your organisation, trained only on data that your organisation has in its records. Public ones, like the ChatGPT you access via your browser, learns from data collected from a wide variety of sources.

It is impossible to know whether there are the correct copyright permissions for the data on which your AI results were based. Looking first at private or closed systems, one cannot assume there are no copyright issues as some data may have restrictions on reuse or reliance by the client; this would need to be taken into account when the AI model is trained to avoid accidental copyright breaches.

Turning next to public AI models, there are a number of ongoing cases in which writers, artists and other parties are asserting a lack of appropriate permissions for the use of their works. For example, there has been recent copyright claims from two artists who claim their work has been used to train AI (Reuters, 2023). However, the position is not straightforward. Readers may be wondering why the position is not black and white, i.e. is it not simply that one has permission to use certain data or works, or one does not have permission. The legal arguments asserted by the AI model companies in justifying their use are more complex than this. This is summarised in a Harvard Business Review article by Gil Appel, Juliana Neelbauer, and David A. Schweidel here: [Generative AI Has an Intellectual Property Problem (https://hbr.org/2023/04/generative-ai-has-an-intellectual-property-problem)](https://hbr.org/2023/04/generative-ai-has-an-intellectual-property-problem).

It is important to note that recent case law in the US has also held that no copyright attaches to an AI result where there is insufficient human input, i.e. copyright cannot attach to something purely produced by an AI model (The Verge, 2023). This may arguably be a question of degree and worth bearing in mind if one is using generative AI to produce works that one wants to be unique to a particular project or client.

Some companies like Microsoft, Adobe and Getty are seeking to reassure potential and current customers of their AI models by announcing the provision of indemnities in the event of any copyright lawsuits (IT Brief Australia, 2023; Getty Images, 2023). Such all-encompassing indemnities are relatively rare and even more rare from software companies, whose terms of use often contain wide ranging exclusions of liability. The interpretation and application of these indemnities remains to be tested but do provide reassurance that the companies in control of the AI models are alive to the issue and seeking to mitigate or resolve it.

It is a "watch-this-space" as copyright law in this area develops. In the interim, consider with your professional advisers how to reflect the use of generative AI in your copyright clauses, e.g. by acknowledging its use but limiting responsibility for unknown copyright breaches, or seeking reassurance that any generative AI results were based only on data the party owns or has rights over.

Confidentiality

Many, if not all, contracts have clauses dealing with confidentiality. Some may restrict sharing of any project data to any individuals outside the project team; others are less restrictive and may prohibit sharing of any project data outside the contracting party organisation. Confidentiality clauses will usually allow disclosure in specific circumstances such as where the data is already in the public forum or required to be disclosed by a court of law.

Inputting data into a public AI model is, in essence, disclosing this data to the public without restriction. It is not realistically possible to delete or remove it, and as the AI model uses this data to train, the AI results for other parties could be based on this data or reveal it to such other parties. This could be in breach of contracts as well as revealing confidential business information to external parties. There have been a number of headlines where staff of organisations have done exactly this (Forbes, 2023). However, it is unlikely staff would do this maliciously but rather, simply without awareness of the consequences. It is worth considering issuing a basic ‘dos and don’ts’ best practice guidance note on the key things for staff to avoid as they innovate and experiment with generative AI.

Reliance and Reliability

Generative AI can have “hallucinations”, where it appears to completely make things up, as one lawyer discovered when he submitted 6 cases provided by ChatGPT in support of his case, only to be told by the judge that they were completely fictitious, and he was penalised for this (BBC, 2023). If one blindly relies on the results provided by generative AI, whether its research results or reformatting an existing document, one cannot blame the generative AI model as a defence for the error or mistake. Generative AI is, like a calculator, a tool at the hands of a user to facilitate and speed up results. It is not a panacea to provide complete automation of tasks that require analysis. For now, clients are paying for and relying on one’s professional services, whatever tools one chooses to assist in making that process more efficient.

Personal Data

The GDPR in EU and UK, and personal data laws in some other jurisdictions, contain strict obligations in the handling of personal data and penalties for failure to comply.

Before inputting any personal data into a generative AI model or an app using generative AI, ensure you confer with the GDPR/personal data specialist within your organisation to check this is not in breach of the relevant regulations. For example, inputting personal data into the public ChatGPT model would likely be a breach of the GDPR because it is inputting such sensitive data into a public forum without the ability to control or delete it, and without falling within any exceptions to allow such disclosure.

Ethics and Bias

Generative AI is trained on existing data, but they can have bias embedded in them. There are many articles and research analysis that suggest such data can have certain bias or unfairness (IBM, 2023). If using generative AI therefore, it is important to bear in mind such potential issues and take measures to mitigate any risks of unfairness or bias. An example could be where generative AI is used to screen job applicants and in 2015 Amazon found their program for reviewing resumes was discriminating against women for technical roles. Ensuring that you test the AI model in different environments and with different uses is important to ensure you are mitigating these issues.

Finally, one could realistically use generative AI in combination with other technologies, e.g. BIM, blockchain, smart contracts or Digital Twins. If there is an intention to do so, it seems sensible to set out clearly within the contract, what these technologies will be used for, the risk allocation for potential issues and the allocation of responsibilities for the necessary processes, e.g. data checking, data storage and data security.

Conclusion

The technology surrounding generative AI, and how it is used, is developing and changing at lightning speed. It is normal for laws and legal principles to lag slightly behind any new technologies, and this is no different. However, this chapter provides practical guidance on how current legal principles are likely to interact with the use of AI. The subtleties of such applications are being developed in court – such as the extent of "fair use" by AI developers of available data without being in breach of copyright – and by statute such as the EU AI Act and the various state laws in the US. One key risk mitigation must be to make parties' understanding, expectations, and risk allocation clear in their agreements with each other. Whilst it is crucial to be aware of one's legal rights and obligations, it is far preferable to agree things between each other, reducing disputes and misunderstandings, than rely only on the ever-changing legal landscape.

Non-exhaustive summary checklist of things to consider:

1. **Before generating AI results or inputting data into a generative AI model:**
   a. **Is confidential data or client data being input into a public generative AI?**
   b. **Is the use of the generative AI model in breach of any confidentiality obligations in contracts, internal policies, or other arrangements?**
   c. **Is there express copyright for the AI results and/or have the risks of a copyright breach been allocated by contract or other method?**
2. **Are quality checks and/or accuracy checks been carried out before relying on and/or using AI-generated results?**
3. **Is there an internal governance process or best practice guide for staff to follow regarding generative AI?**

Chapter 7:

Relationship between AI and Digital Twinning

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Introduction

The way we plan, build, maintain and use our built infrastructure is being transformed by digital technology, data, and new skills. Increasingly these themes are converging from individual domains into a connected Industry 4.0 model. This is realised through the digital transformation of an advanced construction process, delivering real-time decision making enabled by cyber physical systems. Cyber physical systems embed intelligence and cognitive computing capabilities into the design and simulation process of a physical system.

Whilst many industry commentators have different views on what technology and concepts Industry 4.0 contains, we believe that in the context of the built environment, the essential components are those identified in the diagram below:

Disruptive trends in the above are driven by the rise of big data and connectivity, advanced analytics, human-machine interaction, and improvements in construction robotics (advanced manufacture) and logistics across the value chain. These data-centric trends are interdependent and becoming synergistic, amplifying each other's strengths when applied together.

Many organisations are already on a digital journey that has taken them from analogue to digital decisions and are now on the next steps towards predictive, adaptive, and agile data powered by AI.

Additionally, organisations are building on initial digital maturity and increasing their data capabilities where concepts such as Building Information Modelling (BIM) and information management are supporting efficient delivery of capital projects and programmes. This has given many organisations the building blocks to start a data science journey.

However, as organisations, especially asset owners, shift towards whole life asset and system performance, there is an increasing need to adopt digital twinning and AI to support performance measurement, insight and forward investment decision making.

The Synergy Between BIM, Digital Twins, and AI

BIM is defined by ISO 19650 as the "use of a shared digital representation of a built asset to facilitate design, construction and operation processes to form a reliable basis for decisions".

This initial capability and Master Data Management (MDM) approach creates the foundation for Digital Twinning. The term "Digital Twin" can mean different things to different people. Digital Twins vary in complexity, but what sets them apart from BIM is the connection between the digital representation (which could be a 3D model or point cloud) and a physical representation.

BS ISO/IEC 30173 defines a Digital Twin as a "Digital representation of a target entity with data connections that enable convergence between the physical and digital states at an appropriate rate of synchronisation"'.

Case Study: Using AI in Heritage Conservation

A recently funded project with the British Council UK, and the Science and Technology Fund Egypt, built a Digital Twin / AI system for a Heritage Palace in Cairo to underpin the renovation of the building and enhance sustainability of operations. The Principal Investigator of the project was Dr Noha Saleeb and Middlesex University UK.

The overall aim was enhancing country tourism and GDP by creating a model for other touristic sites in Egypt, as well as listed buildings globally. During the project, the researchers aimed to align the five main outputs of the project with all 17 United Nations Sustainability Development Goals (UNSDG's). To achieve that, several off-the-shelf AI tools were utilised in the process of analysing the digital twin continuous feed of live sensor telemetry IoT data. These tools included PowerBI (for statistical analysis dashboards), Midjourney (for retrofit design solutions), SORA (for VR simulations), Chat Mind (for optioneering), Kreo (for cost estimation and prediction), Notion (for time planning prediction and risk management), Nantum (for energy and carbon management), and SinguFM (for facilities data management). While utilising each tool separately reaped value within the project, the project team found that it was not possible to integrate the results of the different tools together, as there was no interoperable platform between them. As such it was recommended that in future projects, a bespoke solution using different algorithms (as mentioned before) would be created to encompass the different functionalities in one solution. Furthermore, a 12 step Strategy for implementing AI on projects/organisations was created as a result of this project, which is detailed in Chapter 3.

Digital Twins are motivated by outcomes, tailored to use cases, powered by integration, built on data (often from the BIM), and acquired from different sources, often in real-time from sensing technologies (IoT/Operational Technology). Essentially, Digital Twins use real-time and historical data to represent the past and present and can be used to simulate predicted future "what-if" scenarios.

These Digital Twins create exceptionally large data sets that are difficult to process using traditional data processing applications. However, without this data the Digital Twins are essentially empty, and the data ingestion helps hydrate them.

Additionally, Digital Twins need a sense making capability to provide insight and support decision making, which is becoming increasingly autonomous. It is at this juncture that AI can be truly useful analysing huge amounts of data. This trilogy of constructs offers huge benefits to the construction sector and organisations especially in optimising asset performance, driving reliability and total expenditure efficiencies.

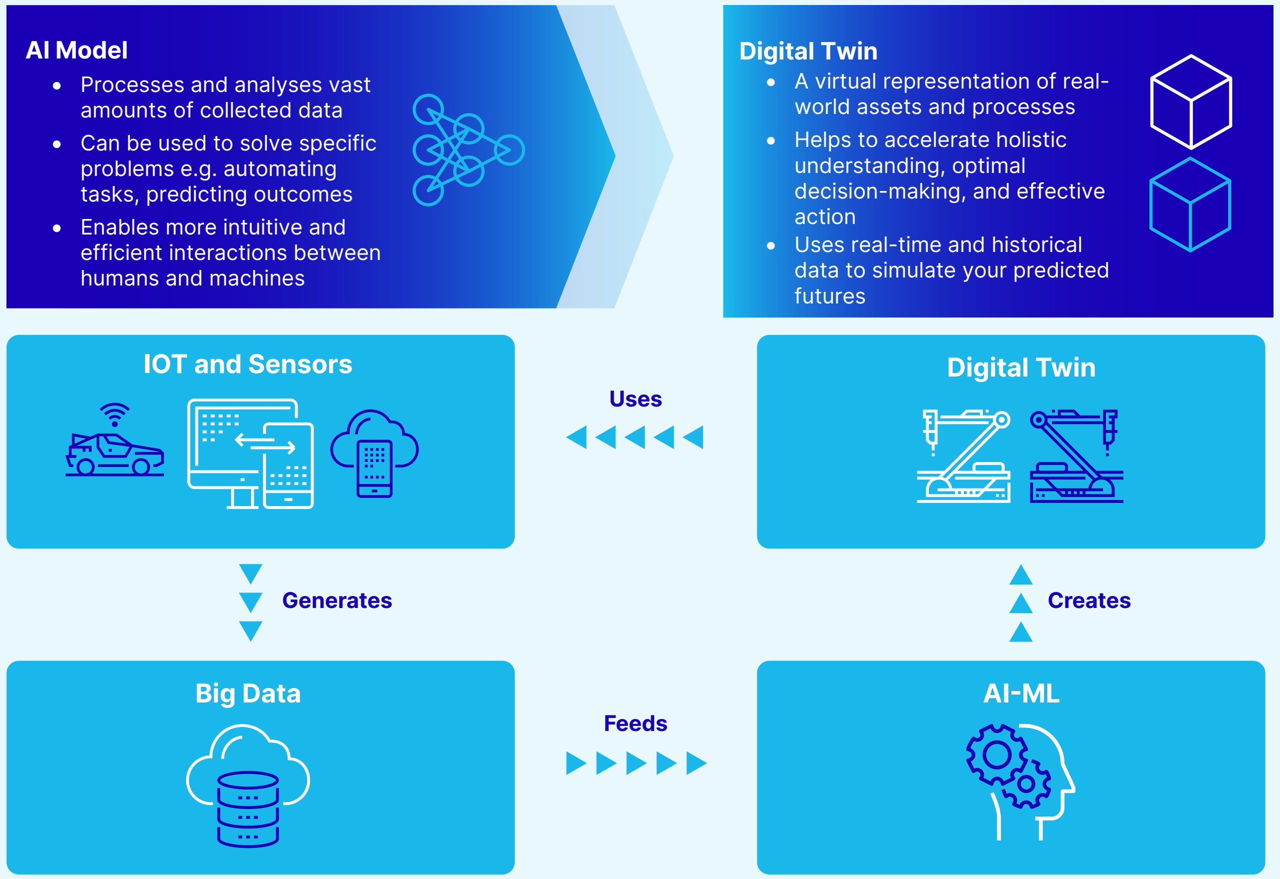
Making sense of data – insight and knowledge

The combination of BIM, Digital Twin and AI creates a powerful synergy that amplifies their individual strengths. Data can be visualised within a Digital Twin viewer that links the model visualisation with real time data. However, the real benefit occurs when the same data is fed into ML and AI engines.

One of the significant contributions of AI to Digital Twin development is its ability to analyse vast amounts of data collected from physical assets. By applying advanced algorithms, AI can identify patterns, anomalies, and potential issues within the data. This analysis enables proactive maintenance and predictive analytics, reducing costs and improving overall efficiency.

It is at this point that the data can be contextualised and used to determine any patterns or to predict future trends, for example, an asset such as a pump is in a pre-failure model. ML and AI provide insight and knowledge into the Digital Twin environment inflating the once-flat basketball.

Figure 1: Example of how AI can provide insight and knowledge into the Digital Twin environment



Learning over time

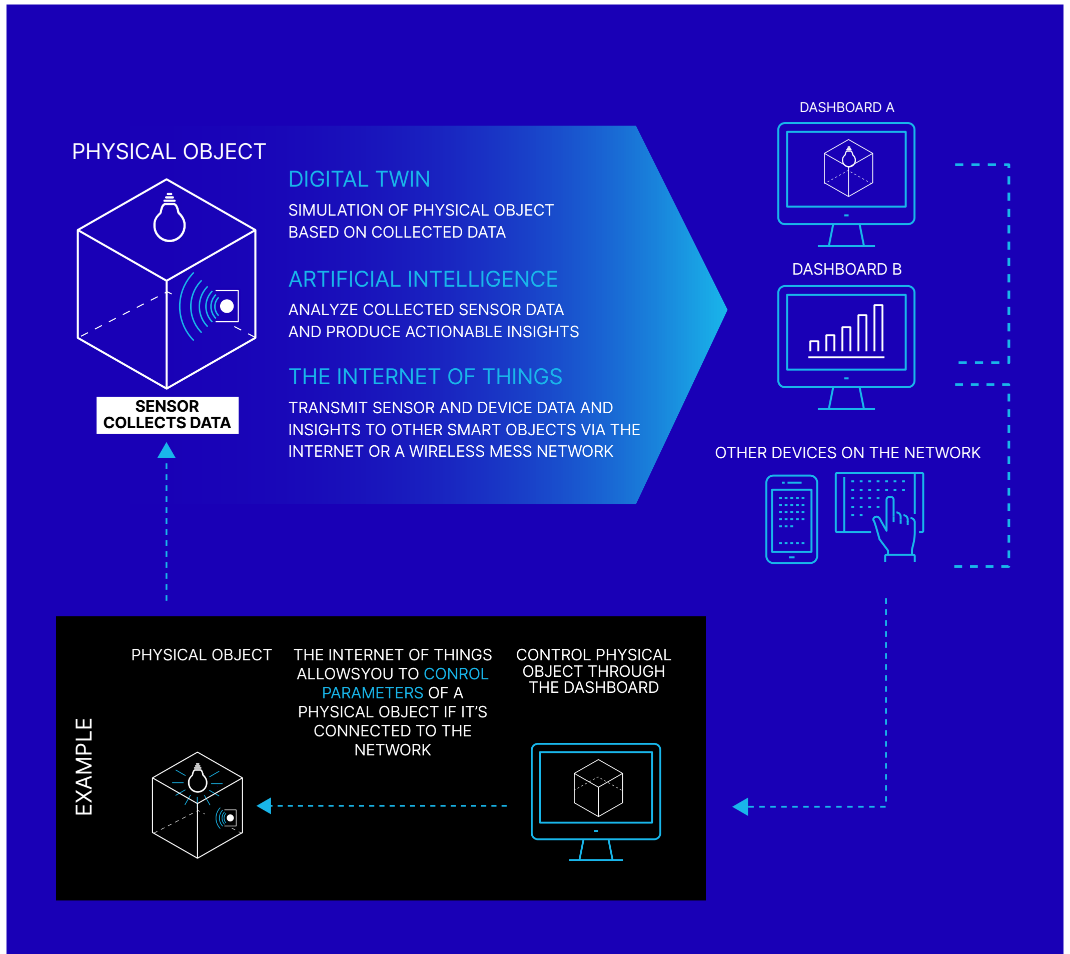
AI can simulate various scenarios and predict outcomes based on historical data. AI algorithms can continuously learn from the data collected by Digital Twins, improving their accuracy and predictive capabilities over time. By leveraging AI, Digital Twins can deliver more accurate insights and predictive capabilities, thereby enhancing their value to businesses. This capability enables businesses to make informed decisions about performance optimisation, resource allocation, and risk mitigation. By leveraging AI's predictive capabilities, companies can optimise their operations and maximise their productivity.

This iterative learning process enables Digital Twins to adapt to changing conditions and provide more precise insights.

Furthermore, AI can automate the analysis and interpretation of data collected by Digital Twins. This automation saves time and resources for businesses, as they no longer need to spend hours manually analysing data. Instead, AI algorithms can quickly process and interpret the data, providing businesses with actionable insights in real time.

Additionally, the synergy between AI and Digital Twin technology enables businesses to focus on strategic decision-making. With AI automating data analysis, companies can allocate their resources towards making informed decisions based on the insights provided by Digital Twins. This shift allows businesses to optimise their operations, improve their competitiveness, and drive innovation.

Figure 2: How AI, IOT and Digital Twin Technology Fits Together



Source: Argentum, How AI, IOT and digital technology fits together

Supporting decision-making

AI supports decision-making and problem statements, which are seen as a critical element of Digital Twin applications. Digital Twins and AI are related in two ways. Firstly, AI can be used to create an enhanced Digital Twin and vice versa; Digital Twins can be used to enable and improve AI applications, especially through its data acquisition layers.

Example 1: AI can be used to create and enhance Digital Twins by using techniques such as data mining, computer vision, and deep learning to collect, process, and analyse the data from the physical objects, systems, or processes. It can also generate realistic and accurate models that can mimic their behaviour and interactions.

Example 2: Digital Twins can be used to enable and improve AI applications by providing a safe and efficient environment for testing, training, and validating AI algorithms and models. For example, a Digital Twin of a car can be used to simulate different driving scenarios and conditions and train an autonomous driving system.

Examples of practical application: Digital Twins can be used to monitor and optimise the construction processes and operational systems. AI can be used to detect and prevent faults (pre-failure), improve quality, and reduce operational costs.

Infrastructure Health: Digital Twins can be used to represent the health status and history of infrastructure, and AI can be used to provide personalised diagnosis, asset optimisation, and failure prevention.

Digital Estates and Smart Cities: Digital Twins can be used to model and manage the urban infrastructure, traffic, energy, and environment, and AI can be used to enhance the safety, efficiency, and sustainability of the campus or city.

Generative AI

Generative AI, which is a type of AI that can create new content and ideas such as design and products, is set to revolutionise digital environments and Digital Twins by transforming them into "Intelligent Environments" and "Intelligent Twins." This integration will be made possible by the augmentation of the human workforce through generative AI, which can even enable "self-driving" Digital Twins and environments. Digital environments refer to the integration of specific capabilities, people, processes, data, and systems through bi-directional closed-loop information flows. They extend across the value chain and can include suppliers, manufacturers, customers, and other third parties. On the other hand, Digital Twins are virtual representations of real-world entities and processes synchronised at a specified frequency and fidelity. They focus on digitally predicting products, services, or processes before they occur.

Generative AI has the potential to benefit digital environments and twins greatly. For example, it can improve the fidelity of Digital Twins by collecting actual information from well-designed digital environments. Additionally, generative AI can ease the complexity of designing and building Digital Twins by orchestrating and integrating various technologies, such as simulation toolsets, IoT and edge devices, cloud computing, and 5G communication. It can bridge gaps in the design, build, and implementation process, improving data quality and increasing speed to value.

There are several real-world use cases for the power of generative AI in Digital Twins. These include data augmentation and synthesis, human-in-the-loop optimisation with natural language interaction, and anomaly detection and fault prediction. Similarly, generative AI can be integrated into digital environments for continuous improvement and real-time data collection, data integration and interoperability, supply chain optimisation, and customisation and personalisation.

AI algorithms and techniques play a crucial role in the development and enhancement of Digital Twin technology. By leveraging AI, Digital Twins can deliver more accurate insights and predictive capabilities, thereby enhancing their value to businesses.

Benefits of Generative AI and Digital Twins

The integration of Digital Twinning and AI offers powerful tools to enhance project planning, quality control, maintenance, sustainability, and overall efficiency. These include:

Project Planning and Management	
Optimised scheduling	
Use Case: By creating a Digital Twin of the construction project, construction managers can simulate different scheduling scenarios to find the most efficient timeline.	**AI Integration:** AI algorithms analyse historical data and current project variables to predict potential delays and suggest optimal resource allocation.
Resource Management	
Use Case: Digital Twins provide real-time insights into the availability and usage of materials, equipment, and labour.	**AI Integration:** AI can optimise resource allocation, ensuring that materials and labour are used efficiently to minimize waste and cost.

Quality Control and Safety Management	
Real Time Monitoring	
Use Case: Digital Twins can monitor the construction site in real-time, identifying deviations from the planned design and quality standards.	**AI Integration:** AI algorithms detect anomalies and potential safety hazards, allowing for immediate corrective actions to prevent accidents and ensure compliance with safety regulations.
Automated Inspections	
Use Case: Digital Twins can automate the inspection process by continuously capturing data from the site.	**AI Integration:** AI analyses this data to identify defects or areas that require attention, prioritising tasks for quality assurance teams.

Predictive Maintenance and Asset Management	
Maintenace Scheduling	
Use Case: Digital Twins of building systems (e.g., HVAC, electrical) can monitor performance and condition in real-time.	**AI Integration:** AI predicts when maintenance is needed based on usage patterns and performance data, scheduling maintenance proactively to avoid breakdowns and extend asset life.
Lifecycle Management	
Use Case: Digital Twins track the entire lifecycle of building components, from installation to replacement.	**AI Integration:** AI provides insights into the optimal timing for upgrades or replacements, balancing costs with performance and reliability.

Sustainability and Energy Efficiency	
Energy Management	
Use Case: Digital Twins can monitor energy consumption patterns in real-time, identifying inefficiencies and areas for improvement.	**AI Integration:** AI optimises energy use by adjusting systems dynamically based on real-time data, reducing energy costs and carbon footprint.
Sustainable Building Design	
Use Case: Digital Twins simulate different design options to evaluate their environmental impact and sustainability.	**AI Integration:** AI proposes design modifications to maximise energy efficiency and minimise environmental impact, supporting sustainability goals.

Construction Process Optimisation	
Process Simulation	
Use Case: Digital Twins can simulate various construction processes, from foundation laying to final inspection, to identify potential bottlenecks and inefficiencies.	**AI Integration:** AI analyses these simulations to recommend process improvements, optimising workflow and reducing project timelines.
Supply Chain Management	
Use Case: Digital Twins provide a comprehensive view of the supply chain, tracking materials from supplier to site.	**AI Integration:** AI predicts supply chain disruptions and suggests alternative sourcing strategies to ensure timely delivery of materials

Infrastructure Health Monitoring	
Structural Health Monitoring	
Use Case: Digital Twins monitor the structural integrity of buildings and infrastructure in real-time, capturing data from embedded sensors.	**AI Integration:** AI analyses this data to detect signs of structural stress or damage, enabling early intervention and maintenance.
Environmental Impact Assessment	
Use Case: Digital Twins assess the impact of environmental factors such as weather, pollution, and seismic activity on infrastructure.	**AI Integration:** AI models predict how these factors will affect the infrastructure over time, informing maintenance and resilience strategies.

Summary

The construction industry is in the midst of a significant overhaul fuelled by digital technology, data utilisation, and skill advancements.

Key components such as BIM, cloud computing, IoT, Digital Twinning, and AI are driving this transformation. What is striking is the symbiotic relationship between BIM, Digital Twin, and AI, where each strengthens the others, amplifying their effectiveness when integrated.

Central to their success is the availability of high-quality, structured data, which is vital for optimal performance within Digital Twins and AI algorithms. AI's role is particularly noteworthy, as it enriches Digital Twins with insights and predictive capabilities by analysing vast datasets, leading to proactive maintenance and cost savings. Moreover, AI algorithms continuously learn from Digital Twin data, refining their accuracy over time and bolstering their value to businesses. This enhanced decision-making support empowers businesses to make informed choices based on real-time insights and predictions.

Practical applications of Digital Twins and AI span various industries, including construction, infrastructure, health monitoring, and smart cities, fostering efficiency and sustainability. Looking ahead, the potential of generative AI to revolutionise Digital Twins is promising, with capabilities to improve fidelity, streamline design processes, and enhance data quality and interoperability. Ultimately, AI's pivotal role in the development and enhancement of Digital Twin technology promises accurate insights and predictive capabilities, delivering tangible benefits to businesses across sectors within the built environment.

Glossary of Terms

The following glossary is taken from the UK Parliament Artificial intelligence (AI) glossary. It is important to note that definitions are not universally agreed and move at a fast pace. However, this glossary complies key terms used in recent POST research on artificial intelligence.

Algorithm
A set of instructions used to perform tasks (such as calculations and data analysis) usually using a computer or another smart device.

Algorithmic bias
AI systems can have bias embedded in them, which can manifest through various pathways including biased training datasets or biased decisions made by humans in the design of algorithms.

Artificial intelligence (AI)
The UK Government's 2023 policy paper on 'A pro-innovation approach to AI regulation' defined AI, AI systems or AI technologies as "products and services that are 'adaptable' and 'autonomous'." The adaptability of AI refers to AI systems, after being trained, often developing the ability to perform new ways of finding patterns and connections in data that are not directly envisioned by their human programmers. The autonomy of AI refers to some AI systems that can make decisions without the intent or ongoing control of a human.

Artificial general intelligence
Sometimes known as general AI, strong AI or broad AI, this often refers to a theoretical form of AI that can achieve human-level or higher performance across most cognitive tasks. See also Superintelligence.

Artificial neural network
A computer structure inspired by the biological brain, consisting of a large set of interconnected computational units ('neurons') that are connected in layers. Data passes between these units as between neurons in a brain. Outputs of a previous layer are used as inputs for the next, and there can be hundreds of layers of units. An artificial neural network with more than three layers is considered a deep learning algorithm. Examples of artificial neural networks include Transformers or Generative adversarial networks.

Automated decision-making
A term that the Office for AI, within the Department for Science, Innovation and Technology, refers to in an Ethics, Transparency and Accountability Framework for Automated decision-making as "both solely automated decisions (no human judgement involved) and automated assisted decision-making (assisting human judgement)." AI systems are increasingly being used by the public and private sector for automated decision-making.

Compute
Compute is defined by the Independent Review of the Future of Compute as 'the systems assembled at scale to tackle computational tasks beyond the capabilities of everyday computers. This includes both physical supercomputers and the use of cloud provision to tackle high computational loads.' Compute is a driver of AI developments.

Computer vision
This focuses on programming computer systems to interpret and understand images, videos and other visual inputs and take actions or make recommendations based on that information. Applications include object recognition, facial recognition, medical imaging analysis, navigation and video surveillance.

Deep learning
A subset of machine learning that uses artificial neural networks to recognise patterns in data and provide a suitable output, for example, a prediction. Deep learning is suitable for complex learning tasks, and has improved AI capabilities in tasks such as voice and image recognition, object detection and autonomous driving.

Deepfakes
Pictures and video that are deliberately altered to generate misinformation and disinformation. Advances in generative AI have lowered the barrier for the production of deepfakes.

Disinformation
The UK Government defines disinformation as the "deliberate creation and spreading of false and/or manipulated information that is intended to deceive and mislead people, either for the purposes of causing harm, or for political, personal or financial gain". Advances in generative AI have lowered the barrier for the production of disinformation, misinformation, and deepfakes.

Educational technology
Technologies specifically developed to facilitate teaching and learning which may or may not encompass AI.

Fine-tuning
Fine-tuning a model involves developers training it further on a specific set of data to improve its performance for a specific application.

Foundation models
A machine learning model trained on a vast amount of data so that it can easily be adapted for a wide range of general tasks, including being able to generate outputs (generative AI). See also large language models.

Frontier AI
Defined by the Government Office for Science as 'highly capable general-purpose AI models that can perform a wide variety of tasks and match or exceed the capabilities present in today's most advanced models'. Currently, this primarily encompasses a few large language models including:

- ChatGPT (OpenAI)
- Claude (Anthropic)
- Bard (Google)

Generative AI
An AI model that generates text, images, audio, video or other media in response to user prompts. It uses machine learning techniques to create new data that has similar characteristics to the data it was trained on. Generative AI applications include chatbots, photo and video filters, and virtual assistants.

General-purpose AI
Often refers to AI models that can be adapted to a wide range of applications (such as Foundation Models). See also narrow AI.

Generative adversarial networks
Generative adversarial networks are a driver of recent AI developments. These are made up of two sub artificial neural networks: a generator network and a discriminator network. The generator network is fed training data and generates artificial data based on patterns in training data. The discriminator network compares the artificially generated data with the 'real' training data and feeds back to the generator network where it has detected differences. The generator then alters its parameters. Over time the generator network learns to generate more realistic data, until the discriminator network cannot tell what is artificial and what is 'real' training data and the AI model generates the desired outcomes. See also artificial neural networks and transformers.

Graphical processing units
These are similar to central processing units, found on a typical home computer. Graphical processing units have been used since the 1970s in gaming applications and have been designed to accelerate computer graphics and image processing. In the past decade, graphical processing units have been increasingly applied in the training of large machine learning models after they were found to be effective in processing large amounts of data in parallel.

Hallucinations
Large language models, such as ChatGPT, are unable to identify if the phrases they generate make sense or are accurate. This can sometimes lead to inaccurate results, also known as 'hallucination' effects, where large language models generate plausible sounding but inaccurate text. Hallucinations can also result from biases in training datasets or the model's lack of access to up-to-date information.

Interpretability
Some machine learning models, particularly those trained with deep learning, are so complex that it may be difficult or impossible to know how the model produced the output (PB 57, PN 633). Interpretability often describes the ability to present or explain a machine learning system's decision-making process in terms that can be understood by humans. Interpretability is sometimes referred to as transparency or explainability.

Large language models
A type of foundation model that is trained on vast amounts of text to carry out natural language processing tasks. During training phases, large language models learn parameters from factors such as the model size and training datasets. Parameters are then used by large language models to infer new content. Whilst there is no universally agreed figure for how large training datasets need to be, the biggest large language models (frontier AI) have been trained on billions or even trillions of bits of data. For example, the large language model underpinning ChatGPT 3.5 (released to the public in November 2022) was trained using 300 billion words obtained from internet text. See also natural language processing and foundation models.

Machine learning
A type of AI that allows a system to learn and improve from examples without all its instructions being explicitly programmed. Machine learning systems learn by finding patterns in training datasets. They then create a model (with algorithms) encompassing their findings. This model is then typically applied to new data to make predictions or provide other useful outputs, such as translating text. Training machine learning systems for specific applications can involve different forms of learning, such as supervised, unsupervised, semi-supervised and reinforcement learning.

Misinformation
The UK Government defines misinformation as "the inadvertent spread of false information". Advances in generative AI have lowered the barrier for the production of disinformation, misinformation, and deepfakes.

Narrow AI
Sometimes known as weak AI, these AI models are designed to perform a specific task (such as speech recognition) and cannot be adapted to other tasks. See also general-purpose AI.

Natural language processing
This focuses on programming computer systems to understand and generate human speech and text. Algorithms look for linguistic patterns in how sentences and paragraphs are constructed and how words, context and structure work together to create meaning. Applications include speech-to-text converters, online tools that summarise text, chatbots, speech recognition and translations. See also large language models.

Open-source
Open-source often means the underlying code used to run AI models is freely available for testing, scrutiny and improvement.

Reinforcement learning
A way of training machine learning systems for a specific application. An AI system is trained by being rewarded for following certain 'correct' strategies and punished if it follows the 'wrong' strategies. After completing a task, the AI system receives feedback, which can sometimes be given by humans (known as 'reinforcement learning from human feedback'). In the feedback, positive values are assigned to 'correct' strategies to encourage the AI system to use them, and negative values are assigned to 'wrong' strategies to discourage them, with the classification of 'correct' and 'wrong' depending on a pre-established outcome. This type of learning is useful for tweaking an AI model to follow certain 'correct' behaviours, such as fine-tuning a chatbot to output a preferred style, tone or format of language. See also supervised learning, unsupervised learning and semi-supervised learning.

Responsible AI
Often refers to the practice of designing, developing, and deploying AI with certain values, such as being trustworthy, ethical, transparent, explainable, fair, robust and upholding privacy rights.

Robotics
Machines that are capable of automatically carrying out a series of actions and moving in the physical world. Modern robots contain algorithms that typically, but do not always, have some form of artificial intelligence. Applications include industrial robots used in manufacturing, medical robots for performing surgery, and self-navigating drones.

Semi-supervised learning
A way of training machine learning systems for a specific application. An AI system uses a mix of supervised and unsupervised learning and labelled and unlabelled data. This type of learning is useful when it is difficult to extract relevant features from data and when there are high volumes of complex data, such as identifying abnormalities in medical images, like potential tumours or other markers of diseases. See also supervised learning, unsupervised learning, reinforcement learning and training datasets.

Superintelligence
A theoretical form of AI that has intelligence greater than humans and exceeds their cognitive performance in most domains. See also artificial general intelligence.

Supervised learning
A way of training machine learning systems for a specific application. In a training phase, an AI system is fed labelled data. The system trains from the input data, and the resulting model is then tested to see if it can correctly apply labels to new unlabelled data (such as if it can correctly label unlabelled pictures of cats and dogs accordingly). This type of learning is useful when it is clear what is being searched for, such as identifying spam mail. See also semi-supervised learning, unsupervised learning, reinforcement learning and training datasets.

Training datasets
The set of data used to train an AI system. Training datasets can be labelled (for example, pictures of cats and dogs labelled 'cat' or 'dog' accordingly) or unlabelled.

Transformers
Transformers have greatly improved natural language processing, computer vision and robotic capabilities and the ability of AI models to generate text. A transformer can read vast amounts of text, spot patterns in how words and phrases relate to each other, and then make predictions about what word should come next. This ability to spot patterns in how words and phrases relate to each other is a key innovation, which has allowed AI models using transformer architectures to achieve a greater level of comprehension than previously possible. See also artificial neutral networks and generative adversarial networks.

Unsupervised learning
A way of training machine learning systems for a specific application. An AI system is fed large amounts of unlabelled data, in which it starts to recognise patterns of its own accord. This type of learning is useful when it is not clear what patterns are hidden in data, such as in online shopping basket recommendations ("customers who bought this item also bought the following items"). See also semi-supervised learning, supervised learning and reinforcement learning and training datasets.

Resources

For those who want to start their journey into adopting and using AI we have included an array of resources.

Understanding i-ReC

The Intelligent regulatory compliance project (i-ReC) was discussed in Chapter 4. The program aims to automate the process of gathering and checking standards using a semantic search engine. Further information about the project can be found here: https://xbim.net/the-i-rec-project-automated-standards-checking/

Setting Standards for Using AI

In order to use AI, standards must be part of the development and use of these tools. The following links have been developed as part of the Innovate UK BridgeAI programme. Both help industry to set standards when using AI.

Foundational standards for using AI in all sectors: https://community.bridgeai.net/blogs/entry/6-introducing-the-foundational-standards/

Key data and digital standards for the built environment: https://community.bridgeai.net/blogs/entry/10-explore-our-key-standards-in-the-construction-sector/

AI Use Case Template

It is important that any potential AI use cases are well considered before starting on its implementation or proof of concept. Essentially, an AI use case is a specific scenario or problem that can be solved or improved by using artificial intelligence techniques.

Our CIOB AI use case template will help to define and describe the use case in a structured and consistent way, covering aspects such as the business goal, the user needs, the data sources, the AI solution, the expected benefits, the risks and challenges, and the evaluation metrics.

The following is a sample AI use case template for your organisation, it can be modified and adapted according to the specific context and requirements of each use case.

Search: https://www.ciob.org/sites/default/files/2024-06/AI%20Use%20Case%20Template.pdf to download the template and an explainer on how you develop an organisational AI strategy.

AI Skills and Data Literacy

To fully leverage the benefits of a connected Industry 4.0 and the themes presented in this playbook will require new skills and data literacy. Professionals need technical expertise in BIM, Digital Twin technology, IoT, AI, and cybersecurity, along with strong data management, analytics, and visualisation skills. Additionally, project management, collaboration, and adaptability are crucial for successfully implementing and leveraging these technologies.
The below table should help you understand what skills are needed, and the data literacy required.

Technical Skills	
Building Information Modelling	AI Integration: Proficiency in BIM software. Understanding of BIM and information standards and protocol (e.g. ISO 19650). Ability to create, manage, and interpret digital models of built assets.
Digital Twin Technology	Knowledge of Digital Twin concepts and frameworks (e.g. BS ISO/IEC 30173. Experience with real-time data integration from IoT systems. Skills in using software platforms for creating and managing Digital Twins (e.g. Bentley iTwin).
Internet of Things (IoT)	Understanding IoT architecture and devices. Skills in deploying and managing IoT sensors and networks. Experience in collecting and processing real-time data from IoT devices.
Data Literacy	
Data Management	Proficiency in data collection, cleaning, and preprocessing. Knowledge of data governance and master data management (MDM) principles. Skills in managing large datasets and ensuring data quality and integrity.
Data Analytics	Ability to analyse large datasets using statistical and analytical tools (e.g., Excel, SQL, PowerBI). Understanding of advanced analytics techniques, including predictive analytics and machine learning.
Data Visualisation	Skills in creating and interpreting data visualisations to communicate insights (e.g., Tableau, PowerBI). Ability to link visual data representations with Digital Twin models for real-time insights.

Artificial Intelligence and Machine Learning	
AI/ML Algorithms	Understanding of machine learning algorithms and their applications in construction (e.g., predictive maintenance, anomaly detection). Experience with AI/ML platforms and tools.
Model Training and Deployment	Skills in training AI models using historical and real-time data. Experience in deploying AI models in production environments to support decision-making.
Cybersecurity	
Data Security	Knowledge of cybersecurity principles to protect sensitive construction data. Skills in implementing security measures for IoT devices and digital systems.
Project Management and Collaboration	
Agile Methodologies	Experience with agile project management techniques to manage digital transformation projects. Ability to work collaboratively in multidisciplinary teams, including IT specialists, data scientists, and construction professionals.
Change Management	Skills in managing organisational change to foster adoption of new technologies and processes. Understanding the human factors involved in digital transformation and how to address resistance to change.
Continuous Learning and Adaptability	
Lifelong Learning	Commitment to continuous learning and staying updated with the latest advancements in digital technology and data science. Adaptability to evolving technologies and industry standards.

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