AI project management

Frameworks and tools for success

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Artificial Intelligence (AI) is becoming increasingly vital for the survival of organisations across many industries. Revealed in a McKinsey Global Survey, there has been nearly a 25% year-on-year increase in using AI in standard business practices as a result of the ever-increasing amount of available data (McKinsey, 2019). Yet the advancement of AI is accompanied by novel challenges such as AI project management. This paper aims to provide a brief overview of AI project management and impart some key advice, ranging from identifying the right opportunities to effective deployment. To this end, the paper is split into three parts. Part I provides an overview of the key challenges facing AI projects and the divergence between managing traditional IT projects and AI projects. It will introduce the concept of uncertainty management and demonstrate why it is a core component to managing AI projects. Part II provides a step-by-step overview of a typical AI project workflow. Finally, Part III delivers some key insights into successfully managing an AI project, from Expert-in-the-Loop architectures to Small Data technologies. The paper will draw on observations from a real life Nexus FrontierTech AI case study, wherein the Sales Quality Assurance process at a large global bank was automated.

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PART I
THE CHALLENGE OF AI PROJECT MANAGEMENT

Introduction

However promising the prospect of applying Artificial Intelligence to your company may be, AI projects often fail after the Proof of Concept phase. However, scaling by extending the scope of automation is a key step to maximising the Return on Investment (ROI) of AI implementation and its strategic impact. Although estimates indicate that AI will add $13 trillion to the global economy over the next decade, only 8% of firms engage in core practices that support widespread adoption. Instead, many firms are only running pilots to apply AI to a singular business process (Fountaine, McCarthy, and Saleh, 2019). This section of the paper will explore some key terminology surrounding AI projects and address obstacles to progressing past the Proof of Concept stage, including the key challenge of AI project management. It will explore the difference between managing traditional IT projects and AI projects, which hinges on the concept of uncertainty management. AI project management is no easy feat and will require a clear strategy and a new skill set in order to reach success.

Key terminology

An AI project manager should have a competent understanding of the different technical concepts that they are likely to encounter in such projects. Therefore, before embarking on the AI project management journey, some key terminology should be clarified. This is true in the projects themselves, as well as in the context of this paper. The below definitions are not intended to represent a comprehensive list, but rather to explain some of the most common concepts used for AI projects.

- ***Artificial Intelligence (AI):*** a machine's ability to emulate human behaviour, including interacting with the environment and problem solving.
- ***Machine Learning (ML):*** the field of learning systems, which involve using statistical methods which allow algorithms to learn by experience and complete tasks without explicitly being programmed to do so.
    - ***Supervised learning*** entails a machine mapping between input and output variables and applying this to predict the results for unseen data.
    - ***Unsupervised learning*** entails a machine receiving inputs only and finding patterns in data.

- ***Deep Learning (DL):*** a type of Machine Learning using many organised layers of machine learning algorithms.

- ***Robotic Process Automation (RPA):*** process automation technology which uses software robots to replicate basic tasks and is used for simple, repetitive tasks such as transaction processing and data manipulation.

- ***Intelligent Automation (IA):*** the augmentation of workflows by combining AI with other processes such as RPA. Together, these technologies can be used for rapid digital transformation and process automation. The most lucrative areas for applying IA are data-intensive and repetitive tasks that machines can do better and faster than humans alone (Tse, Esposito, and Goh, 2019).

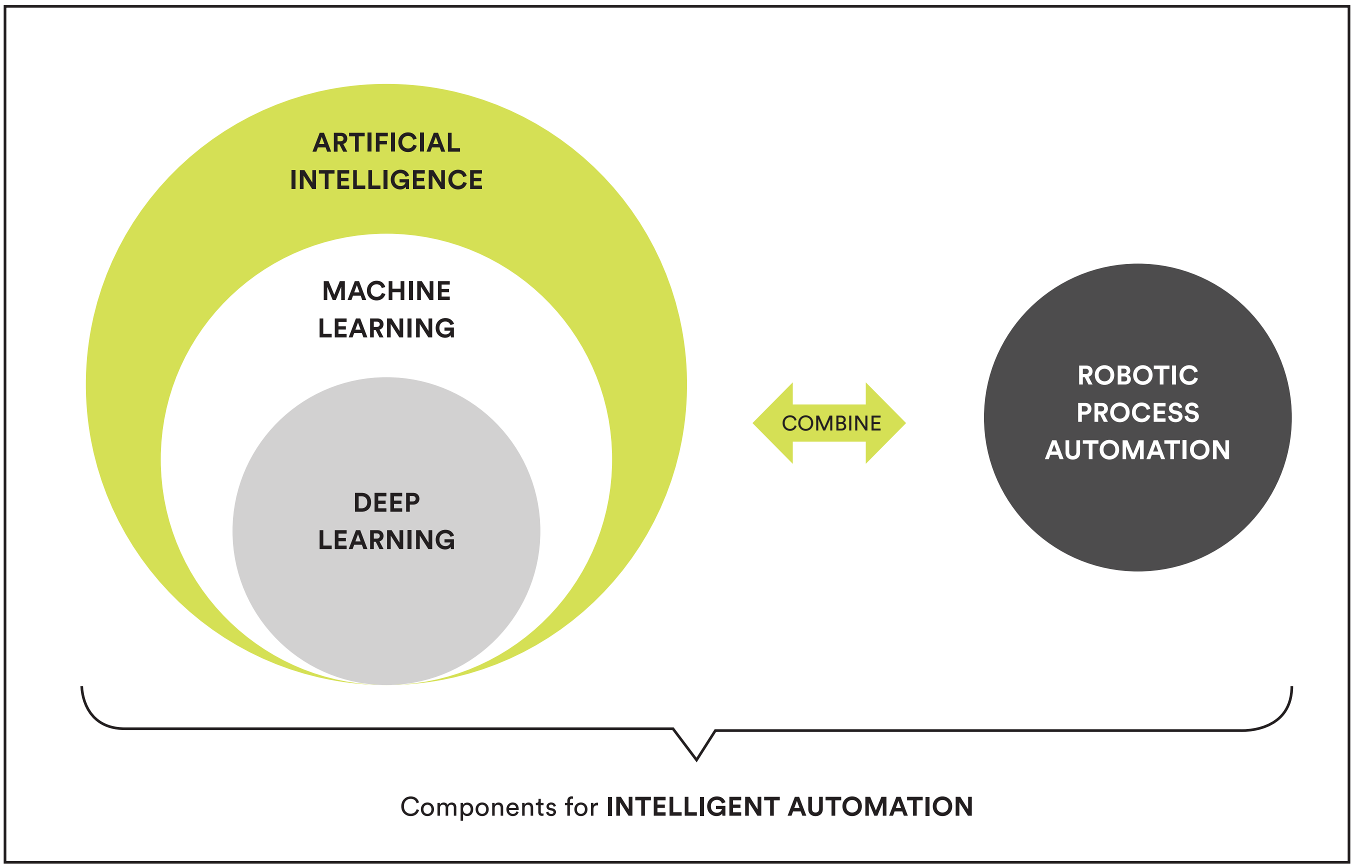
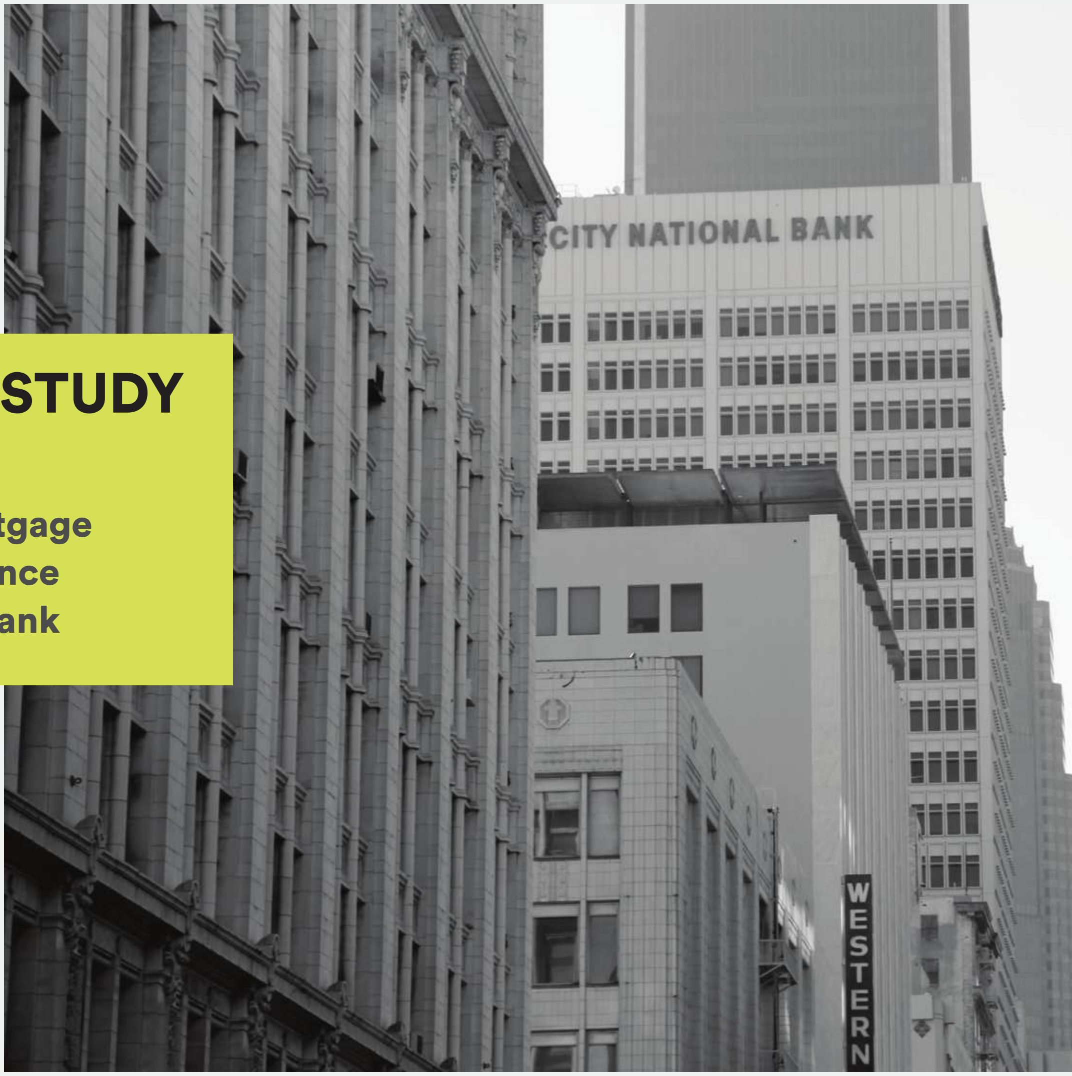


Figure 1: The relationship between Intelligent Automation technologies

AI has become a buzzword lately, and terminologies are often conflated. For example, AI and ML are often used synonymously; however, as indicated in Figure 1 (above), Machine Learning is instead a subset of Artificial Intelligence. Additionally, Deep Learning is a subset of Machine Learning. Robotic Process Automation, whilst not being itself a form of AI, can be combined with different AI technologies for an Intelligent Automation workflow. A common use for RPA in an Intelligent Automation workflow is to automate repetitive tasks to make data available and, in turn, AI can replicate and improve processes based on that data.



NEXUS CASE STUDY

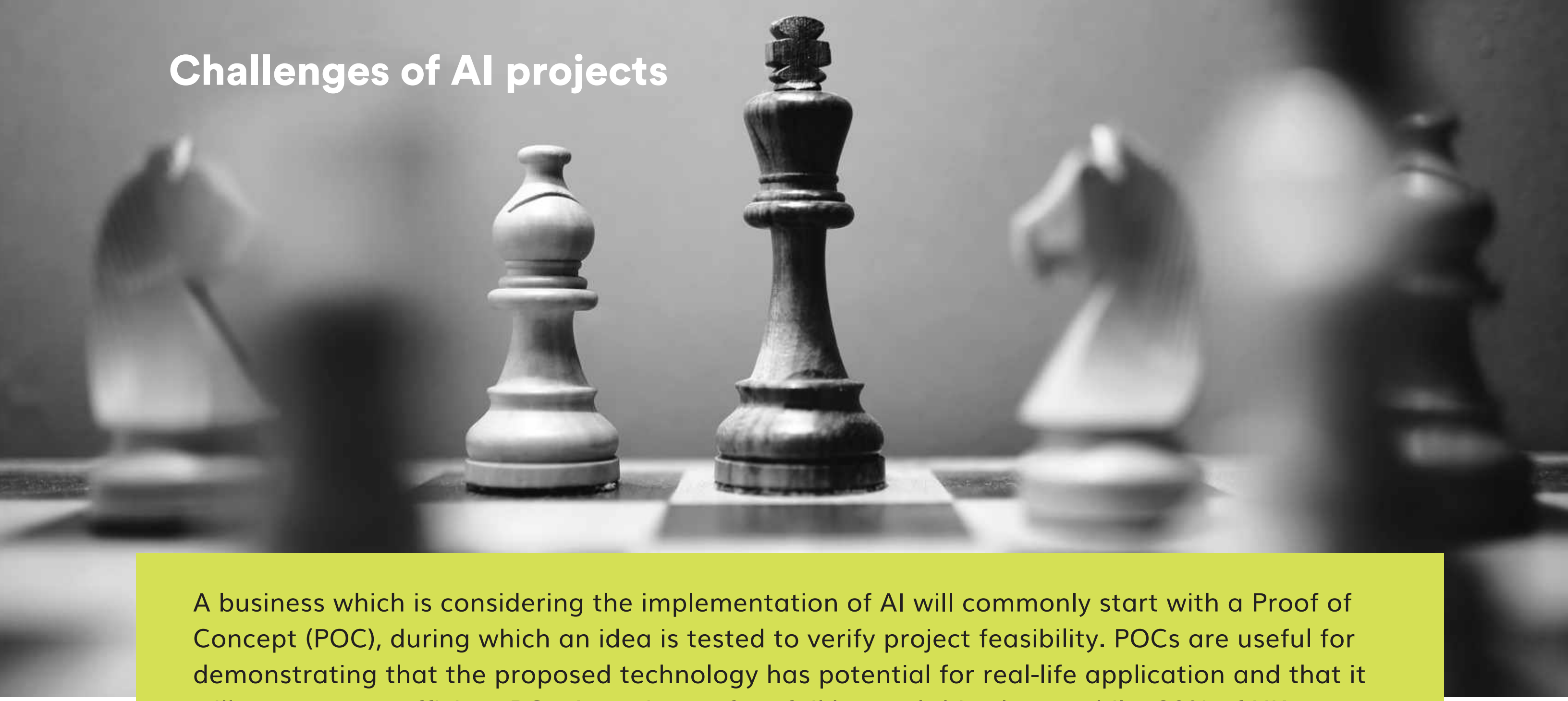
Automating the Mortgage Sales Quality Assurance process at a global bank

Nexus FrontierTech worked with a large global bank to automate their Mortgage Sales Quality Assurance process. The client's Sales Quality (SQ) team was responsible for reviewing completed sales of mortgage products.

The sheer volume of applications, involving around 40,000 documents per month, led to a lengthy, complicated, and mundane checking process. Each application took around four hours to review and required manual extraction of 180 data points across 10 different documents. Therefore, the team could only conduct a limited number of checks amounting to 10-15% of completed mortgage sales and these checks occurred on average 2-3 weeks after the point of sale, leading to compliance gaps. This was a clear example of a highly manual, data-intensive, and repetitive process; in other words, a process ripe for Intelligent Automation.

Nexus worked with this bank to automate this internal compliance process by developing AI models, deployed on-premise, to extract salient data from documents such as bank statements and payslips. The development process was complicated by document availability, quality, and variations, as well as the wide range of document types. Through ongoing analysis, the models were trained to address these difficulties and without access to end-customer data. Nexus demonstrated that AI models can extract the necessary data points from unstructured sources much faster than the previous manual process. Implementing Nexus' solution, the bank is now able to close compliance gaps by checking all completed sales close to real-time. The lengthy and complicated process has been transformed into a speedy and simple one, wherein compliance checkers are directed to the salient points within documents. In turn, this frees up human capacity to focus on anomalies and more complex compliance activity. As the bank moves to large-scale deployment of these AI solutions, it will benefit from a significant increase in ROI whilst increasing the accuracy of checks and reducing operational errors.

Challenges of AI projects



A business which is considering the implementation of AI will commonly start with a Proof of Concept (POC), during which an idea is tested to verify project feasibility. POCs are useful for demonstrating that the proposed technology has potential for real-life application and that it will generate a sufficient ROI. AI projects often fail beyond this phase; whilst 80% of UK executives understand that it is necessary to scale AI across the organisation to stay competitive, 87% of these are struggling to move beyond the pilot to production (Accenture, 2019).

Some factors responsible for this are:

DATA	***Successful AI models rely on quantity and quality of data. However, data is not always available, and it can be spread across multiple applications in various formats. Incorrect or incomplete data which is not prepared to fit into the AI model can lead to low accuracy and bias. Lack of investment of time, resources, and costs into data labelling can be an additional obstacle.***
SKILLS	***Whilst it is necessary to acquire specialists with a deep knowledge of current AI technologies, companies tend to prioritise hiring AI scientists, whilst neglecting the need for system developers and engineers (the AIOps team). However, AI scientists alone do not have the required skill set to fully operationalise AI. Hence, investment of more time and capital is required into building AIOps teams, which will be key in the successful execution and deployment of the project.***
COST	***AI projects and their maintenance can be expensive. For example, without partnering with a vendor, creating an in-house team to create and maintain a production environment can pose a very heavy upfront cost. Some projects fail to achieve an immediate ROI and in many cases, it can be difficult to build a satisfactory business case before visibility of model results.***
INTEGRATION	***It is difficult to integrate AI components into a company's infrastructure and larger IT systems. Many different components may need to be integrated leading to great complexity and additional difficulties when attempting to scale up the environment.***
STAKEHOLDER EDUCATION	***Poor leadership and lack of clear communication can lead to misunderstood requirements and inflated short-term expectations of stakeholders.***
PROJECT MANAGEMENT	***Lack of clear ownership and project leadership can be fatal to the success of an AI project. The AI project manager must understand which stakeholders will be affected by AI implementation and whose support will be needed to drive the change.***

The above factors are interconnected, and having a robust AI project management strategy will feed into solving other problems across the board.

AI project management v. traditional project management methods

Project management is 'the application of processes, methods, skills, knowledge and experience to achieve specific project objectives according to the project acceptance criteria within agreed parameters' (Murray-Webster, 2019). The traditional top-down IT project management approach involves initiating, planning, executing, controlling, and closing a team's work to achieve specific goals and meet specific success criteria within a given timeframe. Dr. Hajime Hotta, Chief AI Officer at Nexus FrontierTech, emphasises that managing an AI project follows a fundamentally different, bottom-up approach allowing AI to draw conclusions from its own rules and processes. The key here lies in the difference between certainty management and uncertainty management.

CERTAINTY MANAGEMENT	UNCERTAINTY MANAGEMENT
Plan all specifications from the outset Specifications are decided and agreed among stakeholders.	**Maximise specification options** Stakeholders align on business goals instead of specifications.
Track progress Progress is measured and reported against the specifications.	**Iterate and validate** Steps along the project lifecycle may need to be repeated and verified.
Minimise uncertainly The goal is to minimise uncertainly from as early as possible.	**Embrace uncertainty** AI models draw conclusions from their own rules and processes.

Figure 2: Certainty management v. uncertainty management

Some of the key differences to these approaches can be found in Figure 2 (above). An IT project manager would be likely to plan and agree on the specifications in advance. The project's progress can be measured against these specifications and predetermined timelines, with the goal of minimising uncertainty. On the other hand, an AI project manager would be more likely to align stakeholders on business goals instead of specifications. This is due to the fact that it is impossible to avoid uncertainties for AI projects; these may arise from all aspects of the business, from data irregularities to regulatory shifts. However, although uncertainties are inevitable, they can be managed. Consequently, it is critical for an AI project manager to leverage on this uncertainty by maximising the specification options and adopting an iteration and validation methodology, elaborated upon below.

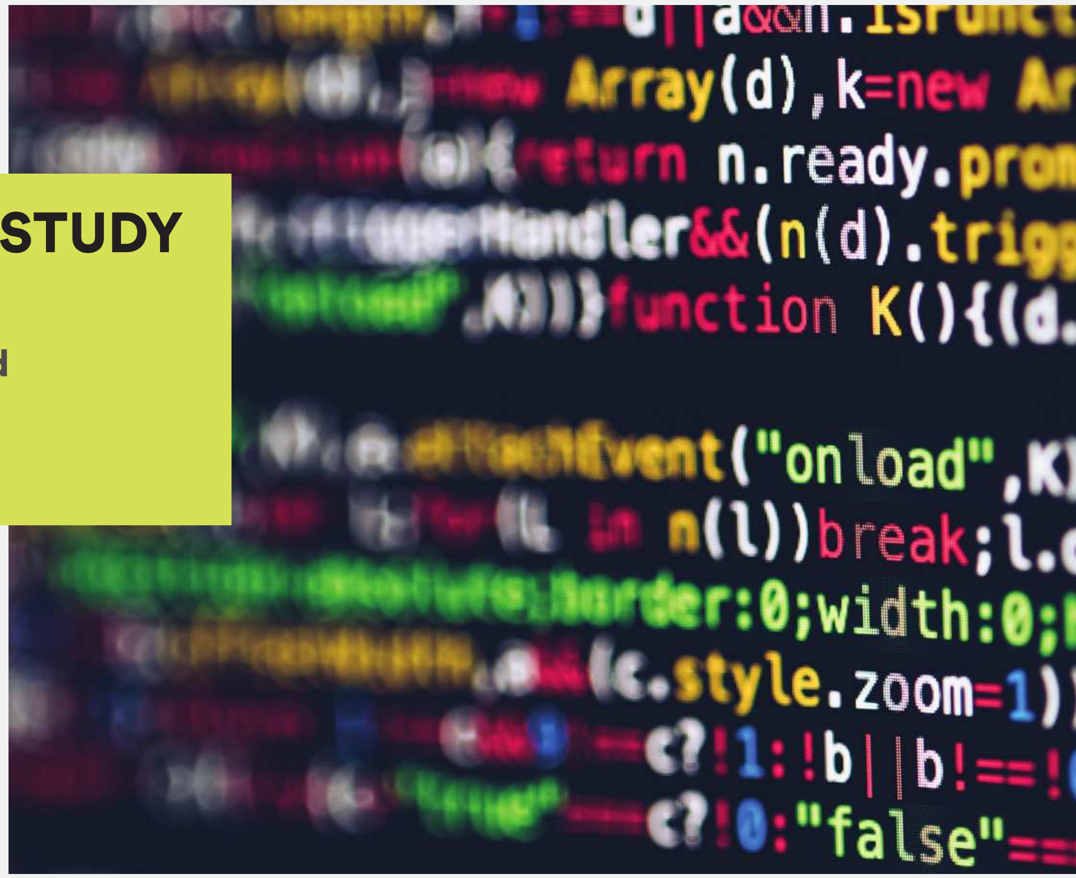
The certainty and uncertainty management division may seem familiar to those who are acquainted with the waterfall and agile project management approaches. The commonly-used waterfall model follows a linear project life cycle wherein the requirements are defined close to the start of the project. Each phase is finished and approved by the client before progressing to the next phase and the team will not return to previous stages without restarting the whole process. The certainty management approach is similar to this in its linear, top-down approach.

On the other hand, agile project management approach is designed to be more flexible and is based on short, continuous iterations referred to as ‘sprints’. Development and testing take place in tandem meaning that it is more possible to amend requirements throughout the project. Uncertainty management aligns more closely with agile principles in its iterative approach and the fact that not all the specifications have to be mapped out at the start of the project.

Due to the difference in approach, an AI Project Manager requires a new set of skills to manage and deliver successful projects. The paper will now explore a basic AI project management framework, followed by some strategies for success.

NEXUS CASE STUDY

Proof of Concept and changing data



The first stage of the project was the POC. Through identification of the data that was the most problematic to extract, we prioritised the extraction of limited fields from 4 document groups.

This activity was time-boxed to 3 months allowing for a go/no-go decision to be made at a sensible time. By being clear from the outset on the scope of this initial phase, we were able to set and manage stakeholder expectations, whilst demonstrating the feasibility and ROI of the project.

As the project progressed, a key challenge was that the input data, as well as requests for extraction points, were changed frequently. This required our models to be retrained accordingly, therefore we had to build them in a way that they could be easily augmented. This required a clear understanding of previous approaches to development to reduce the time and effort spent in identifying the necessary updates. In line with uncertainty management, we needed to take a flexible yet disciplined approach to adapt to changes in priority and data. We adopted shorter testing cycles and feedback loops which allowed us to pivot quickly and we used scenario and sensitivity testing to identify the areas of unknown to control the associated risk. Evidently, this cannot happen in a vacuum and we collaborated closely with the bank to make sure that we were factoring in the details of their process and insights at regular intervals.

PART II
THE AI PROJECT MANAGEMENT WORKFLOW

A basic framework for managing AI projects will be explored, based on the diagram in Figure 2 (below). First, the opportunity for applying AI should be identified, after which design can take place involving data preparation and taking into account functional and non-functional requirements. Following this, the AI models themselves can be built, before being productionalised, deployed, and maintained at scale. This section will address each of these steps in turn.

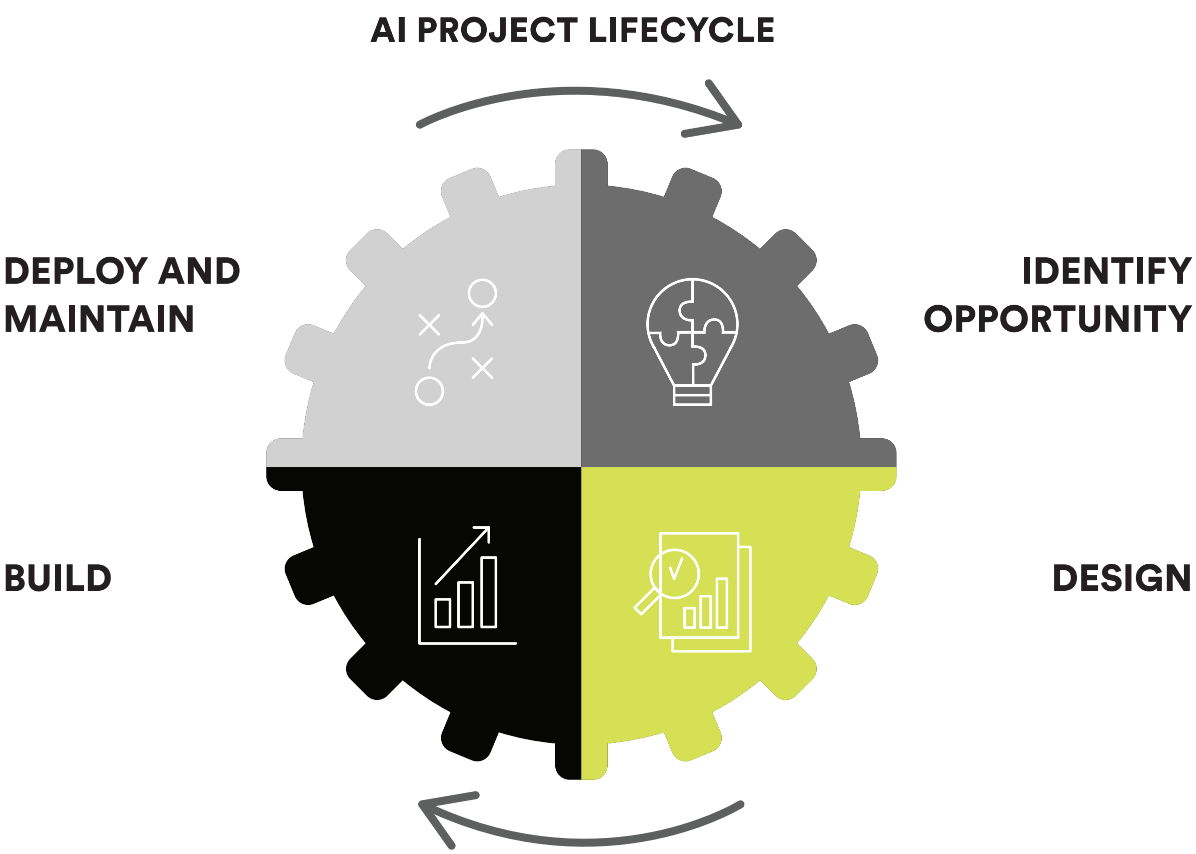


Figure 2: The AI project life cycle

Identifying opportunities

Where should an organisation look to implement AI? They should seek to solve a specific business problem; therefore, not only should the project be technically feasible within the limits of cost, time, and resources, but it must also have a solid business case at its foundation. A good starting point would be to map out the specific tasks within the organisation and explore if any could benefit from automation. These use cases can then be analysed and prioritised. The project manager must have a clear understanding of the problem that needs to be solved and the role of AI in the solution. For example, AI could form the core of the product - or, it could form only a part of it. Context analysis is necessary to discern where it interacts with other components. The project can involve a business analysis phase running in parallel, to allow client input to have a maximum impact and to provide the organisation with a better understanding of their current processes and pain-points. This can lead to a more holistic view of the potential of scaling the solution, collaboratively with different stakeholders, to maximise efficiency and value. This may even enable organisations to re-imagine their business processes or to improve their customer journey in a completely novel way.

Design: analysing requirements and preparing data

Project design involves analysing the solution requirements and preparing the necessary data. The objectives, data sources, roles and responsibilities of stakeholders, and the success criteria should be clearly defined. The latter, against which progress can be monitored, is key. Therefore, functional and non-functional requirements should be considered. Functional requirements should be decided following considerations of the direct requirements originating from user stories. The objective should not be simply to improve accuracy; instead, the consequences of poor accuracy should be considered, such as the intensive manual review needed if the model does not achieve certain accuracy. A better objective could be, for example, that reviewers will not need to correct a result in 80% of cases. Equally important to consider are the non-functional requirements, including system performance, device and browser coverage, the maximum amount of data that can be processed at once, capacity, solution availability and possibility of losing data as well as a backup plan, reliability, maintainability, security, and regulatory compliance (for example, compliance with GDPR).

If possible, a labelled dataset which is compatible with the algorithm should be prepared before starting model building. Data should be evaluated for suitability; one approach is to use criteria-based scoring for example, by differentiating between easy, medium, and hard scenarios. It is important to define the input and the output of the model. Input can come in several forms for example, text, audio, or images, and outputs are the result of passing the data through the model such as detection, extraction, or classification. Data can be annotated by human operators, who define the output for each input data, but an operational process to address any data annotation errors is also necessary.

Training data should also be prepared. In order to avoid overfitting, wherein a ML algorithm fits too much to the training data leading to bias and in turn lower accuracy upon deployment, there should be a representative data set divided into four parts: (1) training data, used for the ML algorithms, (2) validation data, used internally by the training algorithm for parameter tuning, (3) test data, used by the engineers to measure the final performance, and (4) acceptance test data, used to measure final performance.

Model development

A model is configured by choosing a particular type of algorithm, depending on data and requirements. Once the AI algorithm accepts some input, the data is processed and output is returned. The model must be trained, and the amount of time this takes will vary greatly from algorithm to algorithm. The project manager is critical for removing silos in model development, by ensuring that the model developers understand which approach is being used to develop the model to solve the problem. They must also be able to clearly explain this approach for transparency throughout the team. Additionally, they should factor in the time necessary for research effort throughout the project, whilst being mindful of coordinating with the development team to follow up on the progress and overall output.

A rigorous process is necessary to frequently monitor models, re-train, and measure impact. Providing models with the correct information, teaching them what is important, and repetition are critical for improving long-term performance (HBR, 2019). The uncertainty management approach leans on the use of iteration and validation testing loops. Accuracy validation should occur at least three times and an increase of training data may be necessary to improve accuracy since it is not always possible to determine exact data requirements in advance. Hence, throughout the process, there may be many scenarios in which it is necessary to return to previous steps, leading to an iterative approach. Here, the project manager should maintain as much of a business project mindset as a software project mindset, since the results of data and process validation will have an impact on the way in which the AI models are developed.

Progressive test automation, wherein modules are tested one after another, is a vital approach to development. Regression testing, which confirms that a recent program or code change has not adversely affected existing features, should also be adopted with a two-tiered, risk-based approach. High priority cases, for example areas with critical software functions, and medium priority cases, containing exceptional conditions, are always included in the agile regression test suite. On the other hand, low priority cases, covering the remainder of the functionality, are regression tested before major releases to ensure full test coverage. One key differentiator for AI projects compared to IT projects is that the test cases are often not as clear-cut as a pass/fail determination; instead, success is often determined by the percentage accuracy.

Deployment and maintenance

A model could either add a process into the operational flow, for example a further inspection mechanism, or replace processes for more efficient operation. Since a single model can only have limited features, multiple models are often combined into a single process. The data pipeline connects the models to systems and any other software parts. Operationalising the model involves deploying the model and the pipeline to a production environment for application consumption. Key principles to take into account are extensibility, flexibility, and dependability, which will be discussed in more detail below.

The provider should confirm that the models and pipeline fit in with the client's requirements. Hence, ongoing maintenance constitutes an important aspect of managing an AI project, to ensure that business needs are fulfilled and remain fulfilled over time. The models may need to be retrained, additional data collection may be required, and there may be maintenance as the system adapts to its new environment. A process for this should be defined in advance.

The deployment environment is also important to consider. Figure 3 (below) indicates three main environments in which the AI project could be deployed and the advantages and disadvantages to each. The approach chosen for each project should take into account specific organisational requirements and the project manage will need to align with this choice.

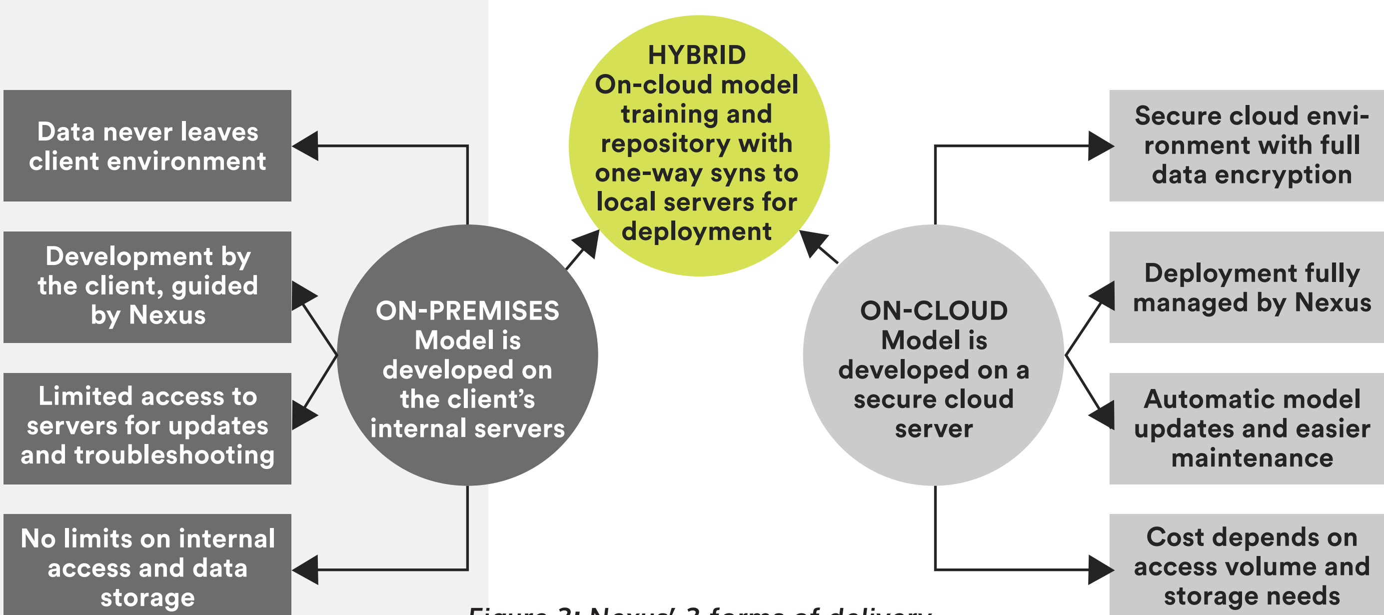


Figure 3: Nexus' 3 forms of delivery

NEXUS CASE STUDY

Testing approach and deployment environment

The models we developed were constantly being updated, due to new data and requirements. This meant that the correctness of the outputs needed to be constantly re-validated.

Without an automated system in place, this would have required a lot of time and effort for human review.

Instead, we developed a configurable and usable testing tool to automate the comparison of actual data and extracted data, resulting in a reduction of time and effort spent on manual testing as well as an increase in accuracy.

A well-managed project will establish what will and will not be shared from the beginning. The client required a fully on-premise solution, since confidential information was at stake and customer privacy was of the utmost priority. Therefore, our system was designed to work in the client's environment without needing to take any data off-premise. This meant following a black-box approach wherein we could not access the client's data. We mitigated this lack of visibility of data by increasing the frequency of feedback communication, including detailed error logging as soon as issues arose.

PART III
TOOLS FOR SUCCESSFUL AI PROJECT MANAGEMENT

Having explored a framework for AI project management, the paper will now introduce some key tools for success for AI project managers. These will include end-to-end management, a robust AIOps strategy, working with cross-functional and inter-company teams, navigating data limitations, and Expert-in-the-Loop architectures.

Managing the project end-to-end

As aforementioned, AI projects often fail after the Proof of Value phase. However, scaling the solution and detecting potential opportunities in new workstreams is a key step to maximising the Return on Investment (ROI) and organisational impact of AI implementation. In fact, on a global level, companies which scale strategically achieved nearly triple the ROI in comparison to non-scaling companies (Accenture, 2019). Therefore, AI project managers must be capable of managing the whole AI project end-to-end, from priming the business for automation to ongoing maintenance.

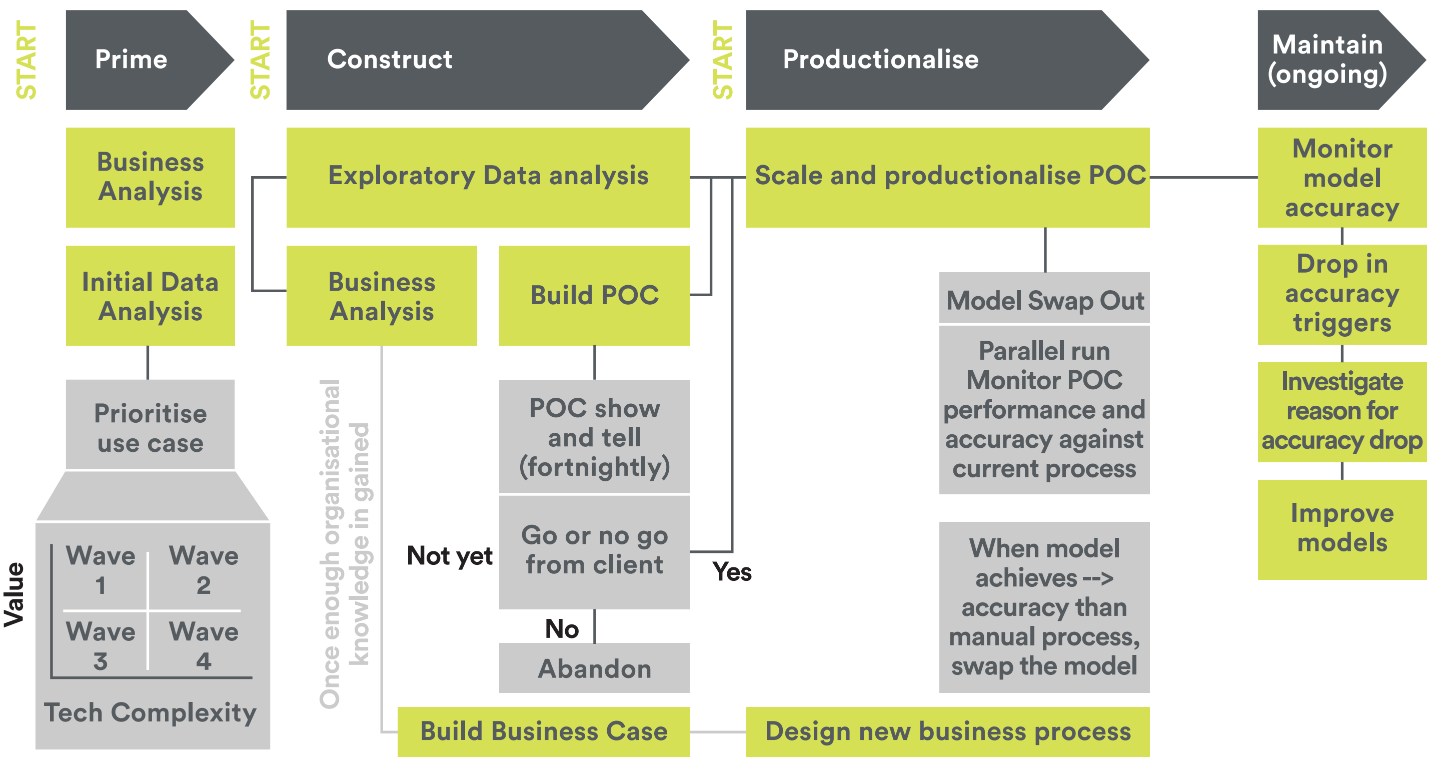


Figure 4: Nexus' holistic framework

Hence, it is necessary to realise the holistic end-to-end value of AI projects. Whereas Part II addressed a basic AI project management lifecycle, Figure 4 (above) depicts, in more detail, what a holistic end-to-end workflow might look like. As shown in the diagram, the first phase may be to prime the business through business and data analysis, wherein use cases can be identified and prioritised by both their value to the business and technical complexity. The next step involves model building, and also involves a business analysis phase running with a POC show-and-tell with the client. Not only does this allow client opinions to have a maximum impact, the organisation will also have a better understanding of their current processes and other pain-points where automation would be beneficial. Following this, the POC is scaled and productionalised; the models replace the relevant manual process when their accuracy is higher. Finally, ongoing maintenance is necessary, wherein drops in the accuracy of models are investigated, leading to model improvements over time.

Alongside the different phases of developing and scaling the model, a business case is created regarding the design of new business processes. This is best done as a collaborative practice with input from different stakeholders, thereby leading to a more informed view of the potential of scaling the solution. Importantly, embarking on an AI project may enable organisations to re-imagine their business processes or to improve their customer journey in a completely novel way. The project manager should coordinate not only the development and deployment of AI models but also the phases running in parallel which involve taking into consideration stakeholder views and finding ways to improve existing processes across the organisation.

The importance of AIOps

AIOps is a 'software engineering culture and practice that aims to integrate software development and software operations' (Tse, Mizuno, Goh, and Esposito, 2020). As previously mentioned, it is critical to take extensibility, dependability, and flexibility into account when deploying AI models in a production environment, where the software is operationalised. The extension of model capability (for example, allowing it to handle more data) or broadening into new competencies (for example, adding a new document type) can lead to a deterioration of performance.

To allow businesses to expand, the AI solution must be able to deliver upgraded models while allowing business processes to continue as usual. On the other hand, having a dependable system means that it will not slow down unacceptably or stop functioning altogether when provided with incorrect or large quantities of data. Additionally, the system must be flexible enough to accommodate changes to business objectives and technical demands. Therefore, it is important to utilise CI/CD, a combination of continuous integration (designing, developing, and testing models) and continuous deployment (monitoring of infrastructure, operations, and releases). This will involve frequent data imports and continuously-updated reporting mechanisms, as well as regular refreshing.

A competent AIOps team which can address these challenges, along with the right production environment, is hugely important. AIOps teams consist of system developers and engineers who have the requisite skills and knowledge to integrate different software components, as well as preparing for potential problems that may arise such as crashes and downtime. Organisations hoping to implement AI have a tendency to invest heavily in AI scientists to the detriment of building a robust and capable AIOps team. However, an AI project manager should not underestimate the importance of these teams, and should instead view them as important tools to facilitate successful deployment.

Working with cross-functional and inter-company teams

Not only is it vital for project managers to be able to manage projects end-to-end, but they must have the capability of bringing in the right skills when they are required. AI projects will have the most significant impact when cross-functional teams are involved, as these will lead to a mix of perspectives and skillsets while ensuring that broader company priorities are addressed. The project team may involve a combination of software engineers, AI developers, data scientists, data engineers, systems architects, infrastructure engineers, testers, data analysts, product consultants, and quality controllers. Access to a Subject Matter Expert (SME), often in the form of a current process owner, is crucial to gain insight into the practical realities of business needs. Additionally, a champion from the client-side will be key to bridging the gap between the IT, product, and operations teams. An AI project manager should carefully consider and leverage the dynamics of working with such a team.

Although the necessity of clear communication is key also for traditional IT projects, AI project managers should make sure to align on the capability of AI models as well as set clear stakeholder expectations to ensure they are on the same page. It is important to engage stakeholders at an early stage and to manage expectations in terms of project scope and the limitations of the solution. To this end, internal and external communications should be aligned so all stakeholders are conscious of the AI strategy and long-term objectives. Additionally, supervisors and managers should be trained on how to manage a mixed team of human and digital workers (HBR, 2019).

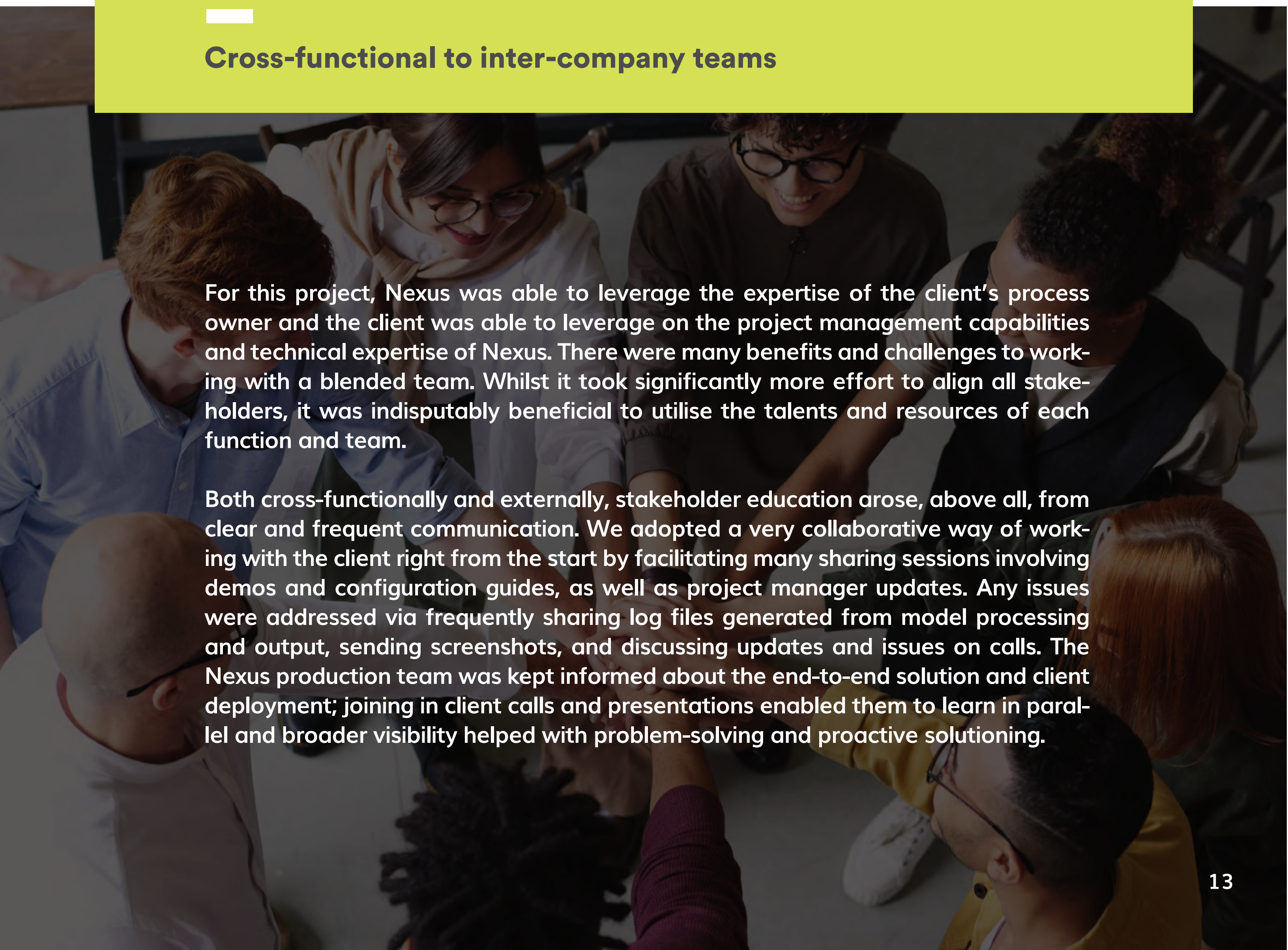
In many scenarios, AI projects involve not only cross-functional but also inter-company teams, wherein stakeholders can be found across different companies.

This can be the best way to leverage different skill sets, for example engaging the expertise client's process owner whilst benefiting from the technical and project management expertise of the company. However, in these scenarios, effective and clear communication is more important than ever.

One vital tool for visibility and education is documentation, accessible by internal and external stakeholders. Two key documents are the Business Requirements Document (BRD) and the Specification Documents. The BRD focuses on the business perspective of the project and contains the details of the business solution, with the aim of aligning stakeholders. On the other hand, specification documents are used for the agreement of the outcome and should cover all the actors featured in the BRD. These documents should be reviewed for comprehensiveness and should be continuously updated.

NEXUS INSIGHTS

Cross-functional to inter-company teams



For this project, Nexus was able to leverage the expertise of the client's process owner and the client was able to leverage on the project management capabilities and technical expertise of Nexus. There were many benefits and challenges to working with a blended team. Whilst it took significantly more effort to align all stakeholders, it was indisputably beneficial to utilise the talents and resources of each function and team.

Both cross-functionally and externally, stakeholder education arose, above all, from clear and frequent communication. We adopted a very collaborative way of working with the client right from the start by facilitating many sharing sessions involving demos and configuration guides, as well as project manager updates. Any issues were addressed via frequently sharing log files generated from model processing and output, sending screenshots, and discussing updates and issues on calls. The Nexus production team was kept informed about the end-to-end solution and client deployment; joining in client calls and presentations enabled them to learn in parallel and broader visibility helped with problem-solving and proactive solutioning.

Navigating data limitations

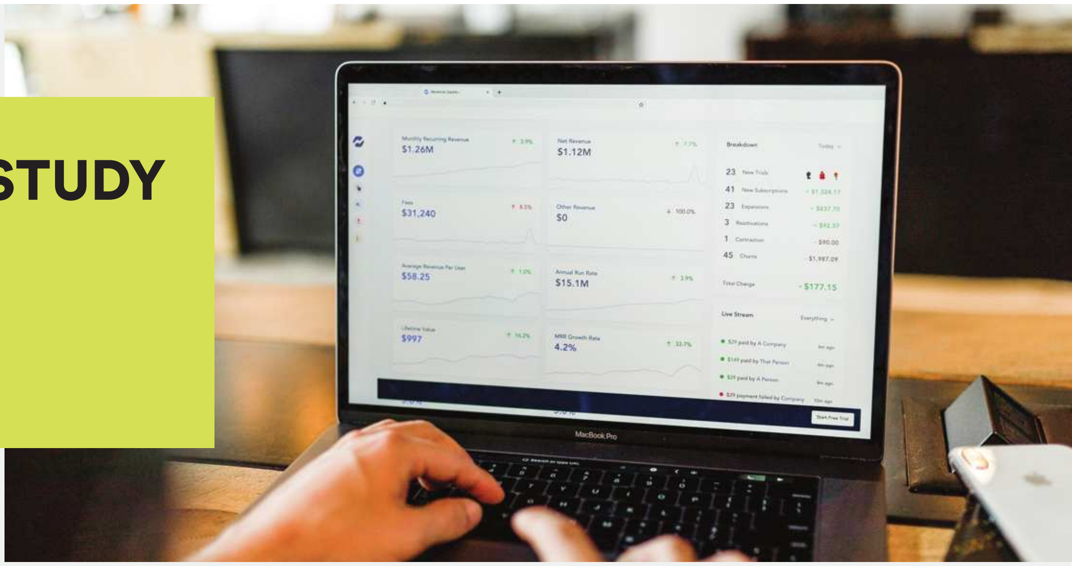
Data is a prerequisite for any AI project. However, data breadth and quality are equally important, for ‘AI hinges on the right kind of data, not just any data’ (Newman, 2018). However, there are many instances in which data is inaccessible or of poor quality. Therefore, a key challenge for AI projects is how to strategically mitigate these issues.

AI-driven propositions often require large amounts of data. There is a high risk of bias when an extraction model is developed based on a small data sample since there is lack of visibility of the actual data quality variation. Hence, it seems logical that it is necessary to have a huge authentic dataset to get started. However, the result of this would be that it would be impossible to create AI projects around areas with high privacy requirements. This calls for innovative solutions to address limited access to data. Such solutions come in part from Small Data technologies, for example, Data Synthesis, a process that creates the training data set. Two approaches can be taken: the programmatic approach wherein engineers generate artificial data for example, using, deep learning models, or the operational approach wherein human data curators manually create both the input and the output. Additionally, it is possible to increase the accuracy of the model by using a dictionary (for example a list of postcodes), which helps the algorithm to better understand input contents and variations.

Furthermore, data quality can vary largely along with formats especially in a world where much data exists in unstructured formats, such as scans and images. Fortunately, a wide range of pre-processing techniques can be employed. These are methods which ensure that the data is ready to go through algorithm processing by reducing the complexity of the data and transforming unclean data so that the machine can more readily interpret it.

NEXUS CASE STUDY

Cross-functional to inter-company teams



To navigate around small initial datasets, we synthesised data according to a variety of different templates. This required a number of hypothetical statistical approaches and involved our team collecting a sample of data from various sources and synthesising similar data in order to achieve the representative size of the data for each model. This also required the synthesis of data of varying quality, which was important for achieving the high accuracy desired. An operational process of quality assurance was necessary to ensure that the synthesised data was correct and fit for purpose.

Since we were extracting from unstructured data, for example in scanned or picture format, it was important to develop models which would maintain a high level of accuracy when data quality variation was expected. Processing, photographic and scanning processes can result in different opacities and defects, including shadows, noises, contrast, saturation, and low resolution which in turn can lead to processing issues. Therefore, we employed a variety of document pre-processing techniques such as de-warping as shown in Figure 5 (below).

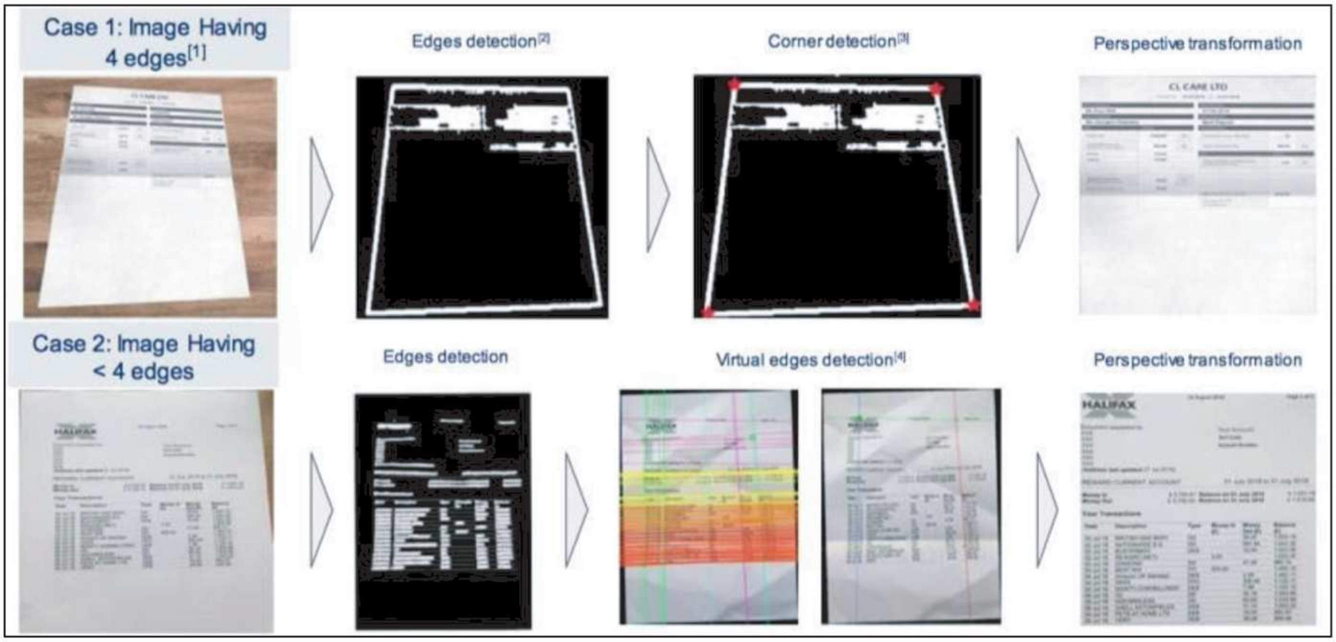


Figure 5: The de-warping technique

Expert-in-the-Loop architectures

The success of an AI project is dependent on how well it integrates into existing workflows. Rationally, persuading users to change their habits in a minor way when the reward is large is easier by far than persuading them to substantially change their habits for an insignificant reward (Eckroth, 2018). As well as benefiting from the SMEs and business analysis skills of the client team, involving end-users in application design increases their chances of adoption. Additionally, this provides the foundation for re-imagining existing workflows, which requires precise project management and change management.

Hence, Expert-in-the-Loop (EITL) architecture, sometimes referred to as the Human-in-the-Loop (HITL), is a vital concept in AI projects. This seeks the best way to incorporate meaningful human interaction into the system to overall enhance the process, under the premise that a system's value is measured not solely in terms of correctness or efficiency, but also by human preference and agency. EITL is able to leverage human agency to optimise system design and increase transparency. This hybrid collaboration often leads to more powerful systems than ever before, since well-orchestrated human-machine interaction can make the system fundamentally better at what it is built to do (Wang, 2019).

Proactive consideration of the broader users and workflow is therefore of the utmost importance. Project managers should carefully consider the practical reality of user interaction with the system. Again, communication is key here since early user feedback can be incorporated into the following version and firms will be able to repair minor issues early on in the process. In some scenarios, systems administrators and engineers may prefer to interact via a Command Line Interface (CLI) since it is easier to connect to other systems. Other users may require a Graphical User Interface (GUI), in the form of a browser application or a dashboard, maximising usability by providing an easy way to manage and make full use of the output. The result is a symbiotic relationship between human and machine: human insights are used to improve the system, whilst automation helps human operators to make better decisions through intelligent insights.

SUMMARY

The rapid growth of automation presents the opportunity for businesses to differentiate and defend their business while gaining a real competitive advantage. AI is a powerful tool that can help to achieve this, as it has the 'potential to create actionable insights through deep data analysis, streamline processes, and map and improve customer journeys' (HBR, 2019). However, managing such a project is no easy feat, due to the multitude of uncertainties that arise, and therefore requires a multi-functional skill set. Hence, AI project managers should be equipped with the right tools and strategies to strive for a project's success. They must have the ability to adapt to dynamic environments with ever-evolving requirements and communicate effectively with a wide range of different stakeholders. They must have a thorough understanding of both business needs and development requirements. Additionally, they must be strategic in navigating issues such as data shortages. In particular, Small Data technologies are a key advancement in tackling areas involving high levels of data confidentiality but with great potential for automation. Careful consideration should also be given to how to holistically expand the scope of automation, with the role of human operators being chief in mind. The necessity for AI project management expertise will only increase with the expansion of AI technology in all fields of business.

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