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DREAM · BUILD · DISRUPT

What's Stopping You from **Implementing AI?**

Check your AI readiness to make smarter decisions.

Read More

A Brief Introduction

In the last 5 years, we have partnered with businesses from diverse industries to develop 30+ AI products. These collaborations brought us face-to-face with pain points troubling CXOs, Founders, Tech Heads, and Innovators while building AI-enabled products.

This e-book is based on our past experience in developing AI solutions for VC-funded startups, high-growth tech companies, and mature Big Tech products.

The e-book answers following questions:

✓ Should I invest in AI? If so, how can I do it smartly?

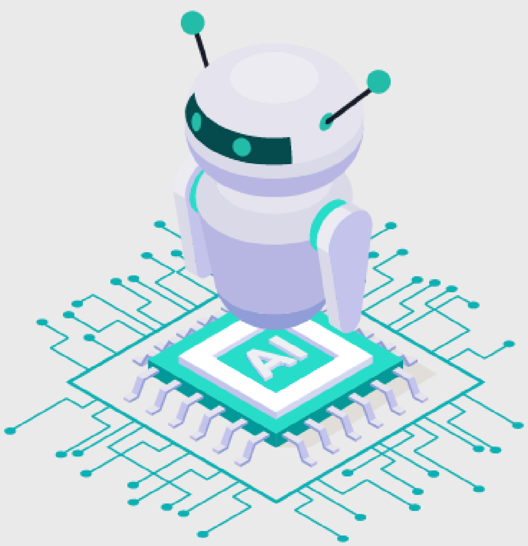
✓ What things to keep in mind before investing in AI?

✓ What are the major implementation challenges faced by AI development teams?

✓ How does implementing AI differ for early-stage, growing-stage, and mature-stage products?

✓ How to check AI readiness and get AI-ready?

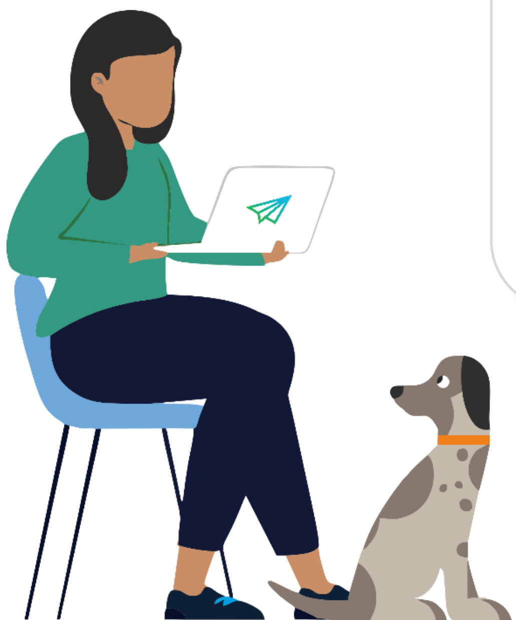
✓ What does a successful AI implementation process look like?



We hope you will get valuable insights from the e-book.

01

Planning to Adopt AI? You’re Not Alone



There's no doubt that COVID-19 acted as a catalyst for AI adoption.

Lately, businesses have begun to view AI as a potential game-changer. As per The AI Journal[1], executives now favor AI as a superior business process enabler with the capability to generate new business models, products, and services.

AI is the new differentiator in the market and no business can afford to miss the bus.

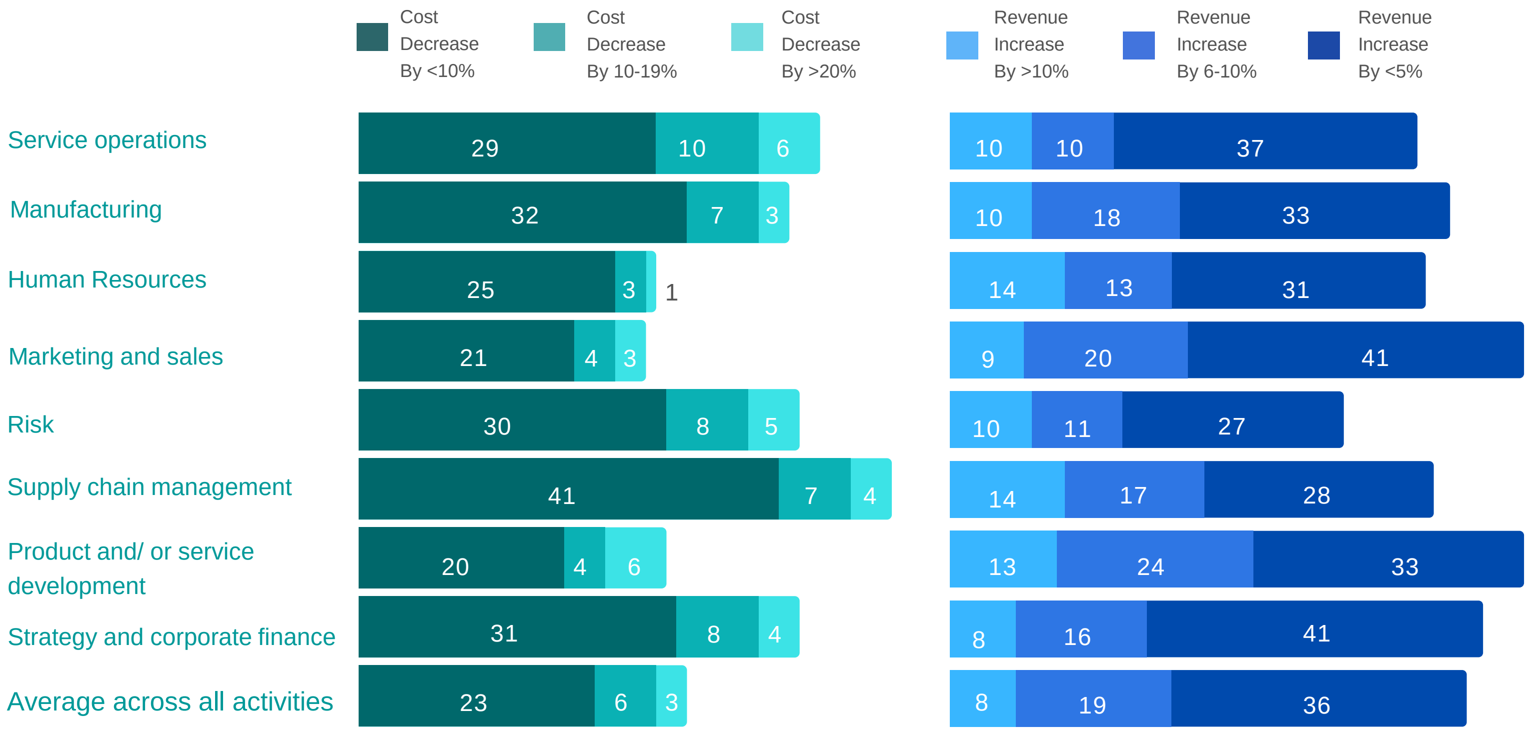
Take Amazon's Sparrow. It is set to transform how logistics work. And if you take a close look at innovations like ChatGPT, Google Bard, DALL-E, Deep Learning chips, and others, they have all started displaying how AI can help beat the competition from Day 1.

Sources:
1) The AI Journal
2) PWC Report.

52% of the companies accelerated their AI adoption plan because of the pandemic[2]

31% of all VC-funding in 2022 went to businesses that adopted AI.

McKinsey’s “The State of AI in 2022” states that costs decreases and revenue increases from AI adoption. The below chart highlight the responses in % of respondents.

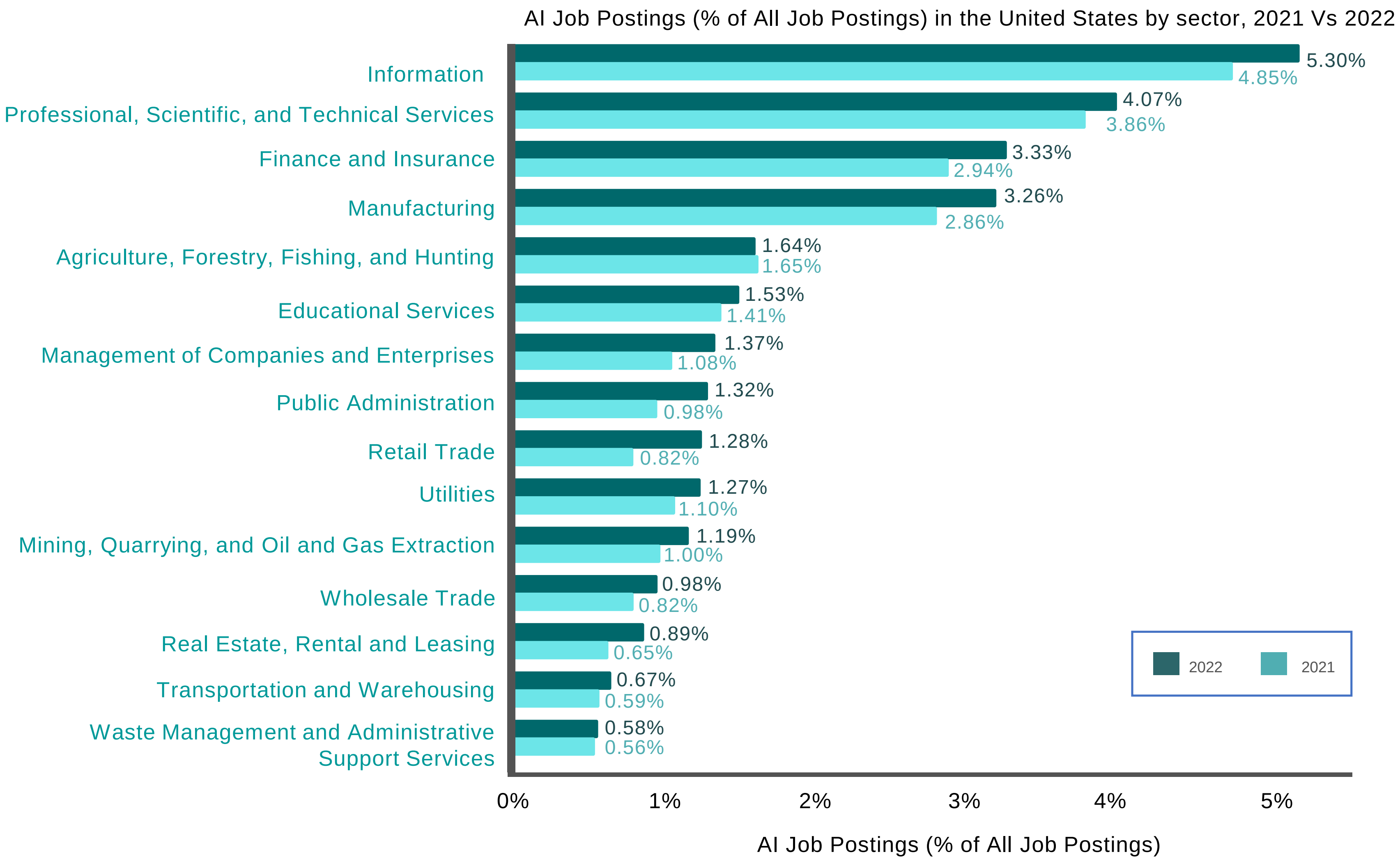


Question was asked only respondents who said their organisations have adopted AI in a given function.
Respondents who said “no charge”,*cost increase, “not applicable” or “don’t know” are not shown.

McKinsey’s “The State of AI in 2022” has some interesting facts about how organizations have adopted AI as an effective value-generation tool. A quarter of the respondents in 2021 have claimed that at least for 5% of their companies’ EBIT, they must give credit to AI.

Source: [McKinsey’s Report on the state of AI in 2022]

The demand for AI experts is on the rise across all the sectors. The below charts provide a comparison of AI related job openings in the companies across the sectors in 2021 and 2022.



Source: [McKinsey's Report on the state of AI in 2022]

02

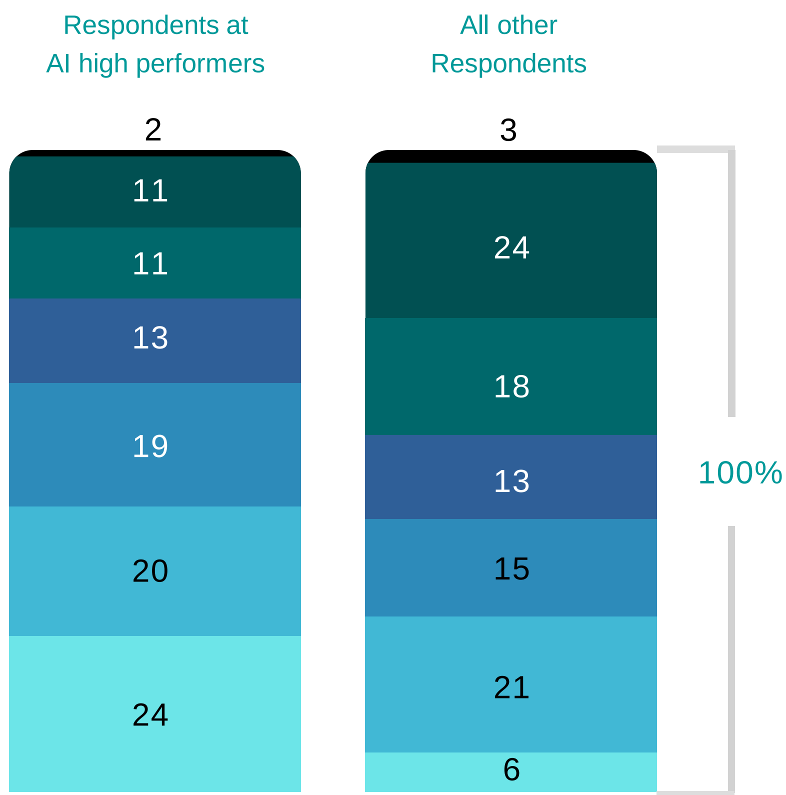
Implementation of AI: A Tough Nut to Crack

Adopting AI isn't a cakewalk especially if you are new to it. Gartner's report on AI/ ML models, shares a similar view.

Element that poses the biggest challenge in capturing value from AI,

% of respondents

- Other
- Strategy
- Data
- Technology
- Adoption and scaling
- Talent
- Models and tools



Models and tools pose the biggest AI-related challenge for high performers, while strategy is a common stumbling block for others.

Source: McKinsey Global Survey on AI, 1684 participants at all levels of the organization, April 11-21-2023

85%

AI models fail to make it to the real world.

Business at different growth stages face different constraints.

- For early-stage products, acquiring enough relevant data to train models poses a challenge. The lack of it can result in accuracy issues for AI models.
- But growth-stage businesses face challenges such as accurate labeling of data, high costs, and privacy concerns with 3rd party AI services, as well as rigid architectures (like monolithic) that may hinder their plans for exponential scale. Poor decisions in this stage can lead to AI model performance issues during product scaling.
- In mature stage products, companies struggle with the complex implementation, longer development cycle time and many face hindrance to change in order to avoid altering a working product. Such companies also face increasing pressure from new competitor products with AI capabilities.

Let's go through the major implementation challenges before touching AI readiness checklist.

Major Challenges

Providing quality domain-specific data can be tough for early-stage products. Specialized domain experts and data fingerprinting techniques are required to break the first barrier.

Absence of Labeled Data

AI models are only as good as the data used to trained them. Generic datasets that are not labeled can't serve the purpose of training AI models effectively.

Data labeling accounts for the majority of data preparation time. Hence, manual data labeling can pose challenges, especially with large datasets. Domain experts and annotation tools are essential to manage this critical process at scale.

Unavailability of Data Pipeline

It's a mistake to assume that once the model goes into production, the job is done. Without a robust data pipeline, measuring the performance of a model in production, iteratively improving it, re-training, and validating it before deployment becomes challenging.

Wrong Choice of Model

Wrong model selection can lead to future issues like unsupported data types, low accuracy, high training cost, and long training time.

Neural network's popularity and its success in recognizing face and other elements prompted a lot of businesses to adopt it and solve business problems. But it demands a larger amount of training data compared to other models, potentially stalling a project indefinitely.

Major Challenges

Tech companies often encounter challenges when integrating AI models with existing products. The focus should be on making AI models production-ready instead of creating standalone proof-of-concept successes.

Wrong Choice of Metrics

The wrong choice of metrics to measure success can make an unsuccessful AI implementation appear like a success initially. Metrics should be selected to align with the business objectives; otherwise, they may not be the right ones.

No Explainability

AI/ML explainability is a key requirement for tech companies, especially in Security, Healthcare, and Fintech domains, due to regulatory requirements. The decision-making process of AI models should be transparent and easy to understand. Else, the models can't be trusted to perform accurately and without bias.

Lower explainability increases the risk of bias, highlights root causes of a given problem more prominently, and makes models less relevant.

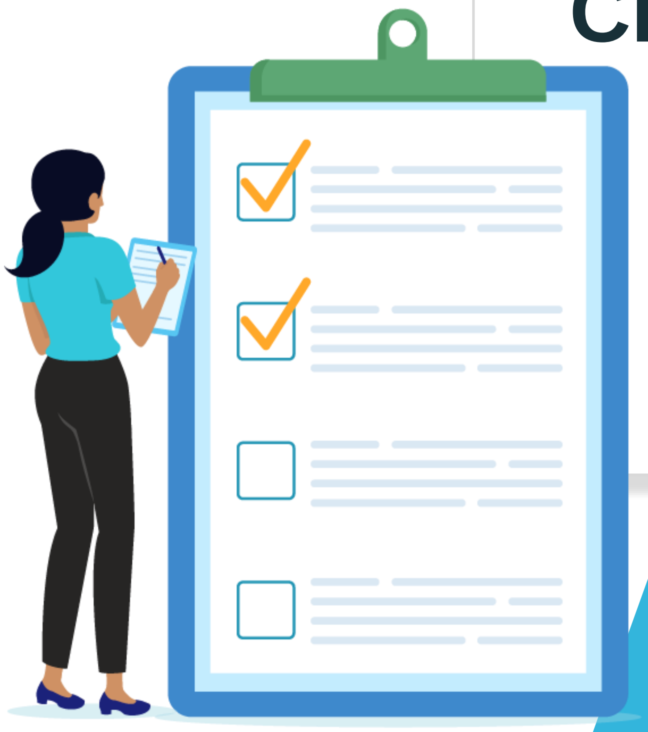
Limited Access to Right Expertise

Data scientists excel at creating mathematical models, while product engineers are adept at implementing solutions. Pairing experienced data scientists with skilled product engineers is a good idea to ensure the proper integration of AI models with the existing product.

But the high cost of hiring in-house data scientists, data engineers, AI architects, and AI developers can make it difficult for early and growing-stage companies to adopt AI, especially if they are uncertain about the potential success.

03

AI Readiness Checklist



Should early stage products adopt AI?

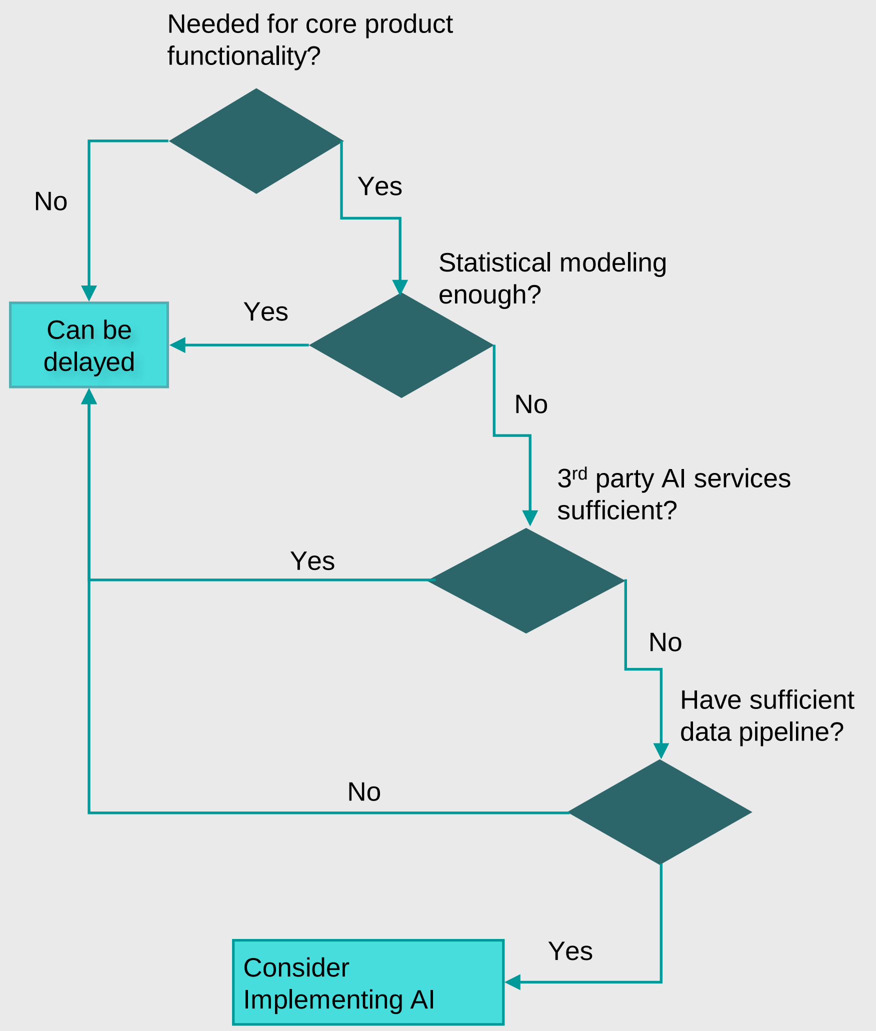
The answer is not straightforward and has multiple factors to consider. But you can start with a simple question.

Is it going to help me achieve my business goals?

In the early stages, your **priority should be to build the core product functionality**. Incorrect decisions can result in the loss of time and resources, both of which are limited. Sometimes, statistical modeling or 3rd party AI services are sufficient at the initial stages.

But, early adoption do come with some advantages:

- Valuable differentiator from existing competition.
- Better chances of funding from VC firms.
- Help in taking data backed decisions from early on.
- Lowered costs due to increasing productivity.
- Unique experience for product users.



Let's go through the AI readiness checklist questions.

Do you have a clear vision of AI solution?

- [x] Are you sure about what business outcomes you want to achieve with AI/ML?
- [ ] Are you clear about the key metrics correlated to the desired business outcomes?
- [ ] Do you have an idea about how the end product is going to look once you are done with AI/ML implementation?
- [ ] Do you have clear product roadmap for the completion of AI implementation?
- [ ] Are you clear about the expertise and resources required for AI implementation?
- [ ] Are you sure your AI models can handle the demands at an exponential scale?
- [ ] Is AI a necessary part of your product strategy?
- [ ] Are you confident about the success of your AI project?
- [ ] Other alternative like statistical modeling, 3rd party AI solutions, not sufficient for the goals?

Do you have the right data strategy?

- Do you have a data-driven culture?
- Do you have domain experts and tools for proper data labeling?
- Do you have sufficient data pipeline for model development and validation?
- Do you have all the required data types for model building and training?
- Have you considered possible future data changes like data type, new data, etc. that can impact your AI model's performance?
- Do you have a data creation mechanism in place that can ensure quality and relevant data for future model training?
- Have you considered all legal compliances and potential bias/ethical issues that can arise during model development?
- If your product is customer-facing, do you have a user feedback system to improve/validate your model?
- If you have limited data or no data, do you have a well-tested data generation strategy and domain expertise?

Do you have the right people/ expertise?

- Do you have resources and people with domain know-how to roll out a full-fledged AI product on time?
- Do you have an experienced AI development team consisting of AI experts, experienced Data Scientists and ML software engineers in your in-house team?
- Do you have an in-house engineering team capable of handling front-end, back-end, UX/UI, DevOps, etc. to build a product properly integrated with AI models?
- Do you have a team that can effectively build and integrate AI/ML models with the existing product?
- Are you planning to train your existing team with AI/ML know-how to engage them in end-to-end implementation?
- Do you have a dedicated AI/ML team who can iteratively improve the AI model post going live into the production?
- Do you have Data Scientists who can develop AI/ML while keeping an eye on engineering aspects, making models that are implementable?
- Are you focusing on creating research papers and patents that can also market your product and add value to your product's valuation?

Do you have clarity on required time and investment?

- Are you aware about the cost factors involved in AI development?
- Do you have a rough estimate of the time required to implement AI?
- Do you have a rough estimate of how much it will cost and have the necessary funds to do so?
- Are you sure simple statistical models or 3rd party AI services are not sufficient to meet the goals that you want to achieve through AI implementation?
- Are you aware about the infrastructure required for developing, training and running AI models?
- Are you clear about the computing performance required to run the AI models, while optimizing cost?
- Are you sure about the total storage capacity required, the type of storage, and future storage demands while considering data privacy and associated costs?

04

Successful AI/ML Implementation

Early stage products

If you have an early-stage product, follow the flowchart discussed in the previous sections to determine if implementing AI makes sense. If the answer is 'Yes,' proceed as mentioned below:

- Early AI adoption can provide a competitive edge and help secure VC funding. It's advisable to outsource AI development to an experienced service provider. This will help you leverage their past experience to get expert guidance while keeping costs down.
- Be cautious, who you select, don't fall for the lowest bid, look for someone who understands your business goals and have a proven history of successful AI development.
- If possible, go for Open source AI models, ChatGPT integrations, Auto ML or use 3rd party AI models provided by Google or AWS that are charged on number of API calls. This is an effective way to manage costs while showcasing AI use cases to VC firms.
- Opt for developing AI models instead of 3rd party solutions if sharing data poses security or privacy risks (especially in Fintech or Healthcare data).

Growth stage products

Implementing at the growth stage comes with its own opportunities. It is easier to arrange the data pipeline, use cases are clear, and easy to integrate with existing product.

Conversely, past tech decisions like wrong core architecture and tech stack selection can make AI adoption extremely complex. The following points are worth considering at this stage:.

- Implementing AI at this stage can help you differentiate your offerings from the competitors. Don't delay; the competition will not wait.
- Data availability should not be an issue at this stage but you need domain experts and annotation tools for correct data labeling.
- Decide on what infrastructure (computing power, storage, networking, security) is required to sustain the AI model.
- Adopt Microservices architecture, it can significantly reduce the AI development complexity. Products with monolithic architecture find it difficult to integrate with AI models.
- Move away from 3rd party AI solutions and try to built your own proprietary AI solutions. At scale, AI services from Google and AWS can become quite expensive.

Mature stage products

At this stage, decision-makers face a dilemma: should they invest in AI and risk altering a working product? Or, should they risk getting outmatched by competitors with AI features?

- Often, hindrance to change a working product's functionality act as a barrier to adopt AI.
- At this stage, AI development is complex. It can become even more complicated if the product is using legacy systems, monolithic architecture, etc.
- AI development will require long development cycles to ensure proper testing.
- While arranging meaningful, relevant data and iterative model training are generally not difficult, integration, on the other hand, is complex.

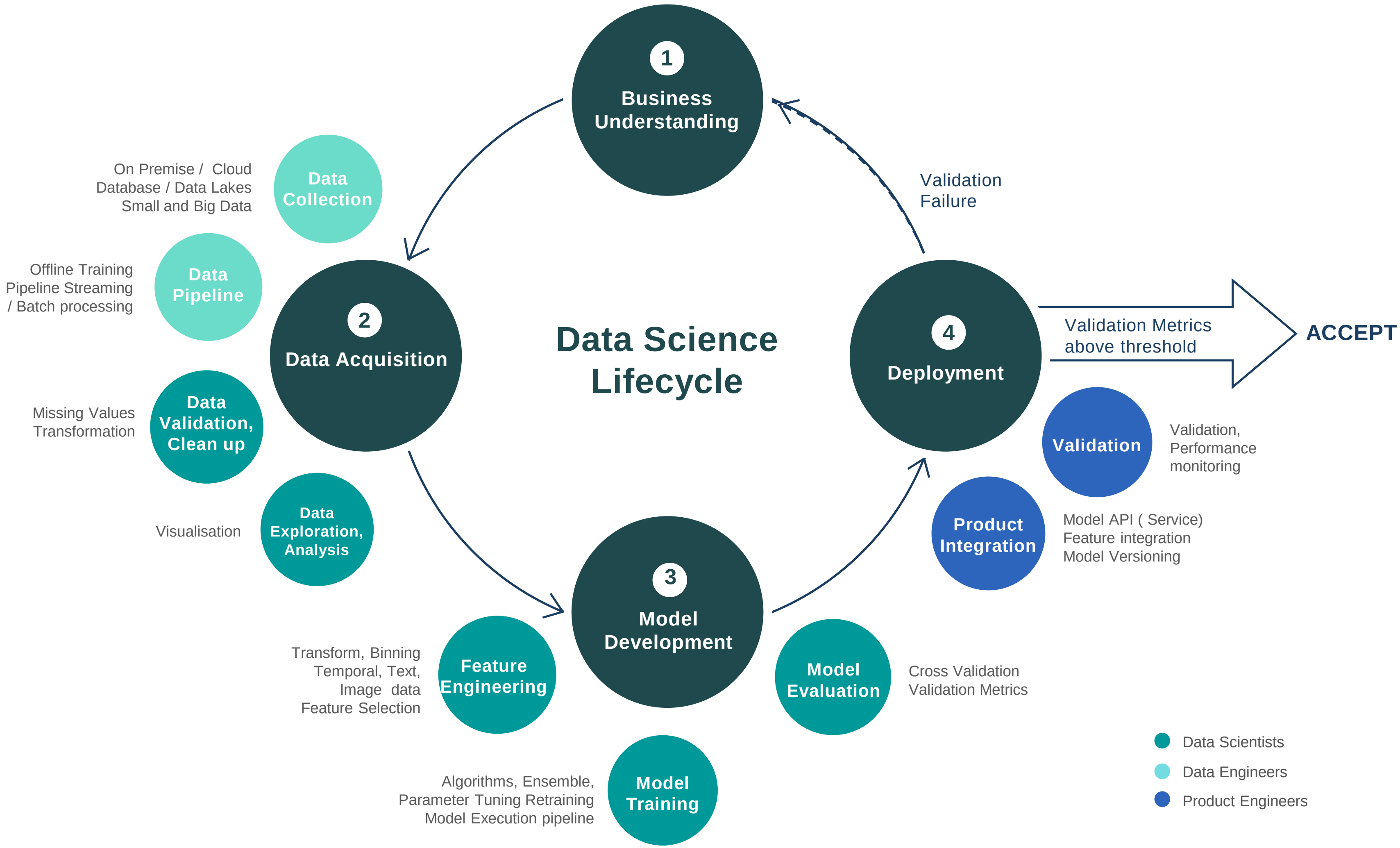
A successful AI implementation needs the right data in sufficient quantity, the right model with continuous iterations, the right infrastructure to sustain, the right team to implement, etc. all working together to achieve a business goal.

Common for all stages

- Decision-makers like founders, co-founders, CTOs, innovators, and tech-heads must have a clear understanding of what real-life challenges they want to solve.
- An iterative approach is good to create scalable, market-ready products.
- There should be a fixed timeframe to complete the project, a proper product roadmap, and a clear picture of how the end product should look.
- Successful AI/ML production depends a lot on an effective data pipeline. For instance, where there is no data or limited data, engineering team should work with a data generation strategy with domain experts.
- Production-ready AI/ML models need Data Scientists and developers in one team. Models might fail if they lacks support from the engineering side.

Let's explore what a successful AI development process looks like.

Successful AI implementation process



About Talentica

Built 180+ Core Technology Products

for large tech companies, VC-funded startups, and ISVs in the last 20 years.

500+ Engineers

Top 2% Indian engineering talent from IITs, NITs, BITs, etc., with median experience of 5.3 years.

Trusted by Customers

60% signups through customer references.

Our NPS score was 75 in the last year.

Google Cloud Partner

Microsoft GOLD CERTIFIED Partner

amazon web services Partner Network TECHNOLOGY PARTNER

Our AI Technology Expertise

Cloud Platforms

aws
Google Cloud Platform
Azure

Data Processing

Apache Spark
STORM
Flink

ML Frameworks

Google AI
Amazon SageMaker
OpenAI

Datastores

Amazon RDS
Google Bigtable
cassandra
Microsoft SQL Server
mongoDB
VERTICA
amazon REDSHIFT
ArangoDB
elasticsearch

ML Libraries

scikit learn
K
pandas

Languages

python
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Looking to outsmart competitors with AI?

With 20 years of product engineering expertise and experience of building 30+ AI products, we can help you leverage AI to create compelling differentiators for your tech product.

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