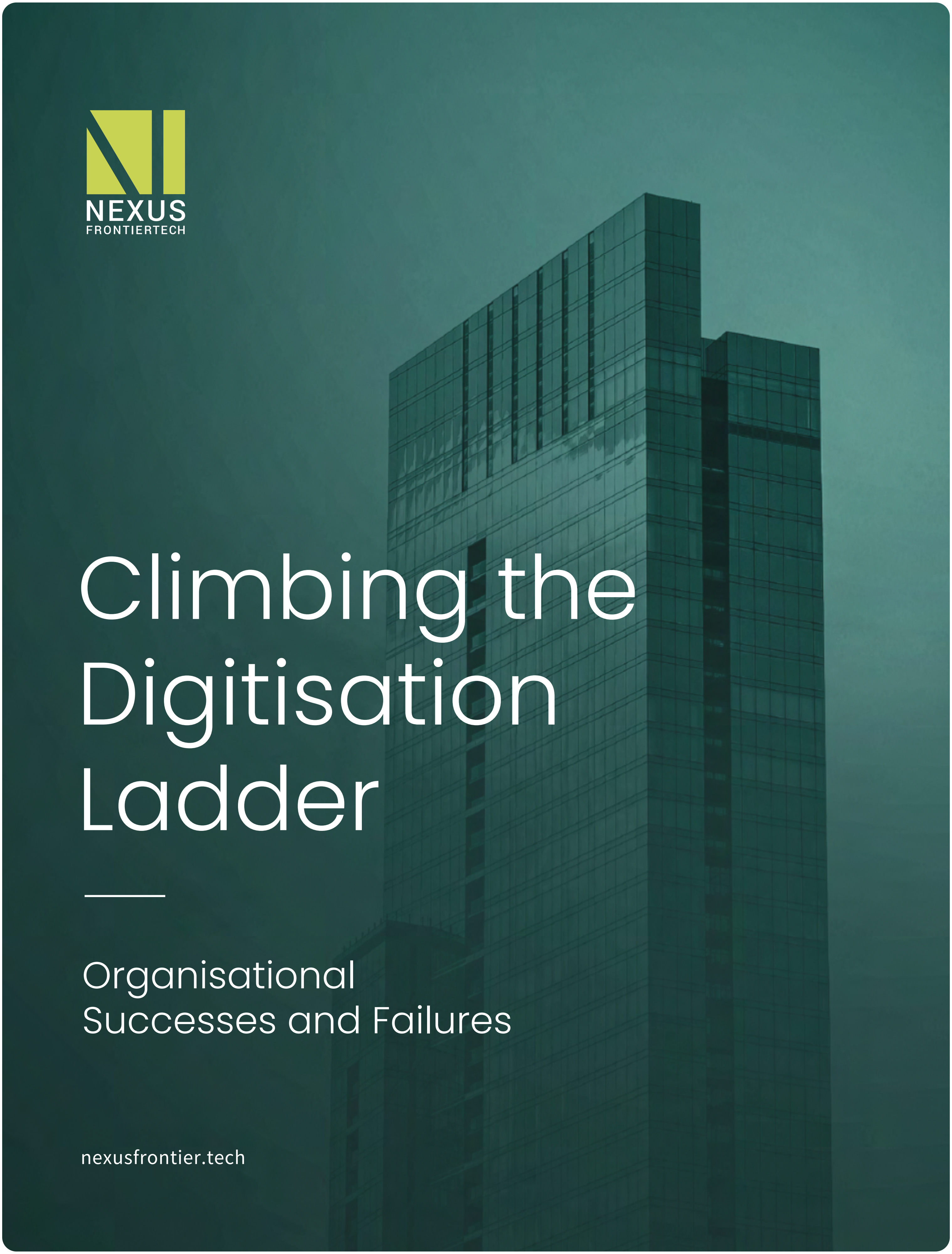


NEXUS
FRONTIERTECH

Climbing the Digitisation Ladder

Organisational
Successes and Failures

nexusfrontier.tech

Preamble

Artificial Intelligence is the latest trend within the business space, and with right reason - Accenture found that in 2021, among executives of the world’s 2,000 largest companies (by market capitalization), those who discussed AI on their earnings calls were 40% more likely to see their firms' share prices increase - up from 23% in 2018. Yet, the successful scaling of artificial intelligence throughout one’s organisation still remains elusive, with over 85% of AI projects failing to capture their intended value. This paper will examine the prominent failure to scale Artificial Intelligence, as well as discuss the reasons behind this failure and how to address them, illustrated by a few Nexus FrontierTech case studies. Through this paper, it is the author’s hope that businesses can successfully scale AI and climb the digitisation ladder.

Introduction

"Artificial intelligence is one of the most profound things we're working on as humanity. It is more profound than fire or electricity."

SUNDAR PICHAI,
Google CEO

His feelings are shared by many. An Economist survey found that 3 quarters of surveyed executives would have AI "actively implemented" in their companies within the next three years. Across boardrooms and offices around the world, innovation teams and executives are scrambling to ascend the digitalisation ladder in pursuit of greater efficiency, and artificial intelligence represents the most promising frontier there is.

McKinsey's Global State of AI in 2021 survey saw 56% of respondents reporting adoption of AI in at least one business function, suggesting the increasingly widespread usage of AI in business. In many minds, now is the prime opportunity to capitalise and take advantage before one becomes a laggard. But yet, the promise and allure and hype of artificial intelligence often conceal numerous pitfalls, turning ostensibly rosy and encouraging projects into fool's gold.

HISTORY OF AI

The concept of "artificial intelligence" was first conceived almost seven decades ago, at a Dartmouth College conference in 1955, by 20 of the field's eventual pioneers and leaders in research. Various revolutionary programs were developed to explore the potential of reducing human intelligence through step-by-step symbol manipulation, otherwise known as 'SymbolicAI'. From Allen Newell and Herbert Simon's "Logic Theorist" program finding philosophical proofs to Terry Winograd's SHRDLU reading basic English, the future seemed bright for Artificial Intelligence. Simon, a Nobel Prize-winning political scientist and economist, was led to declare:

"Machines will be capable, within twenty years, of doing any work a man can do."

However, Simon and the rest of the AI community's unbridled optimism turned out to be painfully wrong. Following a decade of lavish spending but little to show for it, both public and private support for AI research ended painfully with the Lighthill report in 1973:

"Most workers in AI research and in related fields confess to a pronounced feeling of disappointment in what has been achieved in the past twenty-five years. Workers entered the field around 1950, and even around 1960, with high hopes that are very far from having been realised in 1972. In no part of the field have the discoveries made so far produced the major impact that was then promised."

DISREPUTE/ DIS-TRACTION OF AI

What followed was known as the "AI Winter", where funding was cut and the field of Artificial Intelligence fell into disrepute up till the 21st century, only interrupted by the "Expert Systems" boom and bust in the 1980s. But why did such a concept with seemingly limitless potential fail? In part, this was owing to the usage of the symbolic approach, where researchers and scientists pursued high-level representation of human cognition, eschewing subsymbolic approaches that are more basic and easier to achieve. These subsymbolic approaches are the approaches that brought AI back in fashion in the 21st century and the approaches we now use today, be it mathematical optimisation or neural networks.

This, in turn, was perhaps due to the "unbridled optimism shared by Simon and the AI community as mentioned earlier. Instead of focusing on specific solutions to specific problems that would produce specific results, initial research was focused on achieving a general imitation of human intelligence, which resulted in unverifiable and impractical results. Moreover, by jumping straight into the deep end without grasping the basic tenets of artificial intelligence and developing the technologies and infrastructure required, AI researchers of the 1950s were essentially biting off more than they could chew. Consequently, such research into Symbolic AI was deemed unsuccessful and slowly ground to a halt.

The resurgence of Artificial Intelligence was only brought about by learning from the errors of the past.

INCEPTION OF AI

Through the emergence of new technologies and new technical developments, artificial intelligence has burgeoned in the 2010s, where the number of enterprises utilising AI in the workplace has grown 270% from 2015 to 2019. The emergence of new techniques like deep learning has brought endless possibilities and potential to artificial intelligence, while elsewhere, the development of cloud computing together with exponential increases in computing power has shattered previous technical limitations for artificial intelligence. The Internet of Things, the Data Age, Big Data - from tweets to telemetry, the snowballing of the quantity of data we have available has correspondingly led to a proliferation in what AI and the aforementioned data-hungry deep learning can do.

Artificial intelligence has finally shown some real-world, tangible potential for the business world after its storied history of booms and busts, promises and disappointments. In the last decade, artificial intelligence has been shown to have a multitude of benefits and applications in a variety of fields.

The list of applications runs long:

- Forecasting
- Price setting
- Inventory stocking
- Job Applications

McKinsey estimates that "60 percent of occupations have at least 30 percent of constituent work activities that could be automated." Beyond the widespread coverage/potential of AI's applications, the benefits it brings are tremendous to boot. The numbers don't lie.

$15.7 trillion

Global GDP gains from AI by 2030

A PriceWaterhouseCoopers study projected that AI could increase global GDP by a whopping $15.7 trillion by 2030, a figure sure to convince even the most stubborn of sceptics. The revolutionary impact of artificial intelligence has been so prodigious and broad that Sundar Pichai, Google's CEO, was compelled to proclaim:

> ***"AI is one of the most important things humanity is working on. It is more profound than, I don't know, electricity or fire,"***

AI failures & implications

The failure of AI projects may seem like small mistakes yet have big costs. Just ask Amazon, which was forced to scrap its AI recruiting tool after it was found to be biased against women. Or Stephen Kelly, who was forced to resign from his chief executive role at Sage after a flawed digital transformation and migration to the cloud. Evidently, critical mistakes can backfire and have much greater negative consequences than imagined, making safety and security a necessity in the implementation of AI projects.

SCRUTINISING SCALABILITY

Conversely, executives can't afford to be put off by such security risks, for the costs of lagging behind are far greater. Be it due to stubbornness or apprehension, history is filled with countless companies and executives who have fallen by the wayside after failing to keep up with the times. Hence, always seeking to stay a step ahead of the competition by being "early adopters" of the latest technologies remains imperative for businesses all around the world.

Indeed, this is the mindset adopted by the large majority of businesses as they all seek to dive head first into the AI fountain of wealth, where global spending on AI is estimated to reach $57.6 billion in 2021, according to IDC.

However, they face a different challenge - promising ideas failing to deliver substantial tangible returns. Due to a myriad of causes, what were once transformative proposals eventually stagnate into vanity projects.

As Accenture found in 2019, over 80% of companies were stuck in this trap of experimentation without production, constantly stymied in various Proofs-of-Concept (PoCs) with neither actual solutions to problems nor stakeholder buy-in. This is a pervasive problem shared by executives - Accenture found that 76% of executives across the world "know how to pilot, but struggle to scale across the business." Perhaps more worryingly, the same survey found that in the case of inability to scale AI, 84% of executives wouldn't be able to achieve their enterprise growth objectives while 75% claim they risk going out of business within 5 years.

A clear and tangible disadvantage can now be seen by the inability to scale, perhaps proving Gartner right when they predicted in 2018 that 85% of AI projects wouldn't be able to deliver their intended value, similarly citing high risk and confusion in adoption as the two main reasons for failures.

Yet, scaling remains a rare success for businesses. While nine out of 10 businesses have investments in AI technologies, only a sixth of those nine reports widespread usage and production of these AI technologies. Another study found only 20% of 3,073 respondents had scaled AI-related technology.

The problem doesn't lie with the AI - despite their omniscient, all-knowing stereotype popularised by Hollywood, Gurdeep Singh of Microsoft instead describes AI as "idiot savants", capable of menial yet mind-boggling tasks like data extraction or web scouring but unable to go beyond that. In truth, the ultimate power still resides with us - AI is a tool that only serves to accelerate business processes and decision-making. Michael Chui of the McKinsey Global Institute elucidates this best:

> *"Ultimately, the value of AI is not to be found in the models themselves, but in companies' abilities to harness them."*

Technological Issues

The problems are numerous. First off, we have to consider the implications of scaling - as things scale up, different aspects become more exponentially interconnected and complicated; the problems and implications multiply, and this is no different for AI projects as well.

FORSAKING TECHNICAL FEASIBILITY EN ROUTE TO SCALING

One such problem that might occur is neglecting to consider technical feasibility in terms of the availability and ability of computer infrastructure. OpenAI found in 2018 the amount of computational power used to train the largest AI models was doubling at 7 times the rate in 2012, equalling a 300,000-fold increase in total.

As mentioned earlier, as firms progress from small subsets of data to real-life datasets with millions of data points and scale-up algorithms, the increase in processing and storage requirements from before is likely to be exponential. Consequently, businesses could find themselves facing immense computing resource needs, be it in the form of processing or memory usage, especially if they fail to consider the technical feasibility of AI solutions they intend to implement.

PASSING THE INTEROPERABILITY TEST

Equally important is the integration of said AI solutions into the existing IT systems of the business. For the successful implementation of your new AI solution, the ability for software to work seamlessly with the rest of your business systems and processes is essential. In the POC stage, models are often standalone, requiring only one isolated system to train, retrain and test. But after moving on to deployment, AI models now require integration into the data pipeline/flow with multiple other systems. Having to constantly update itself, the AI model has to receive data from upstream systems and transfer data to downward systems to continue operating smoothly.

It is clear that without careful consideration and management of infrastructure and integration, the immense amounts of data and algorithms could result in latency issues, bottlenecks and high operating costs. At best, this could result in an underwhelming investment, at worst, this could result in an entire system failure. Remember Sage and their failed migration to the cloud?

AI enthusiasts will remember the "Netflix Prize", a great archetype of the failure to consider technical feasibility in the scaling of AI projects. In 2006, Netflix launched the Netflix Prize, a 1 million dollar open innovation competition to develop the best recommendation algorithm for the company. Yet the prize winner, which saw a 10% improvement in accuracy, was never implemented. Why? Well according to Netflix,

"the additional accuracy gains that we measured did not seem to justify the engineering effort needed to bring them into a production environment."

Simply put, while the initial Proof-of-Concept was easy to carry out for team Pragmatic Chaos, the infrastructure and integration costs were too much once put into production. Besides that, Netflix had already pivoted towards online streaming from the initial DVDs the recommendation algorithm was meant for. But it's safe to say, 15 years later, the lessons of the Netflix Prize still remain painfully relevant for companies attempting to scale up deceptively simple AI algorithms.

DATA IS THE NEW OIL

Beyond infrastructure, data is a key concern affecting the scalability of AI as well. Data is growingly recognised as "the world's most valuable resource", crucial in delivering both business value and improving processes. A recent study by the MIT Sloan Management Review found that data is considered by managers as one of the key enablers in leveraging the potential of AI. Yet, a 2022 survey showed organisations continue to struggle to become data-driven, with only 26.5% having achieved this goal, and only 19.3% having established a data culture.

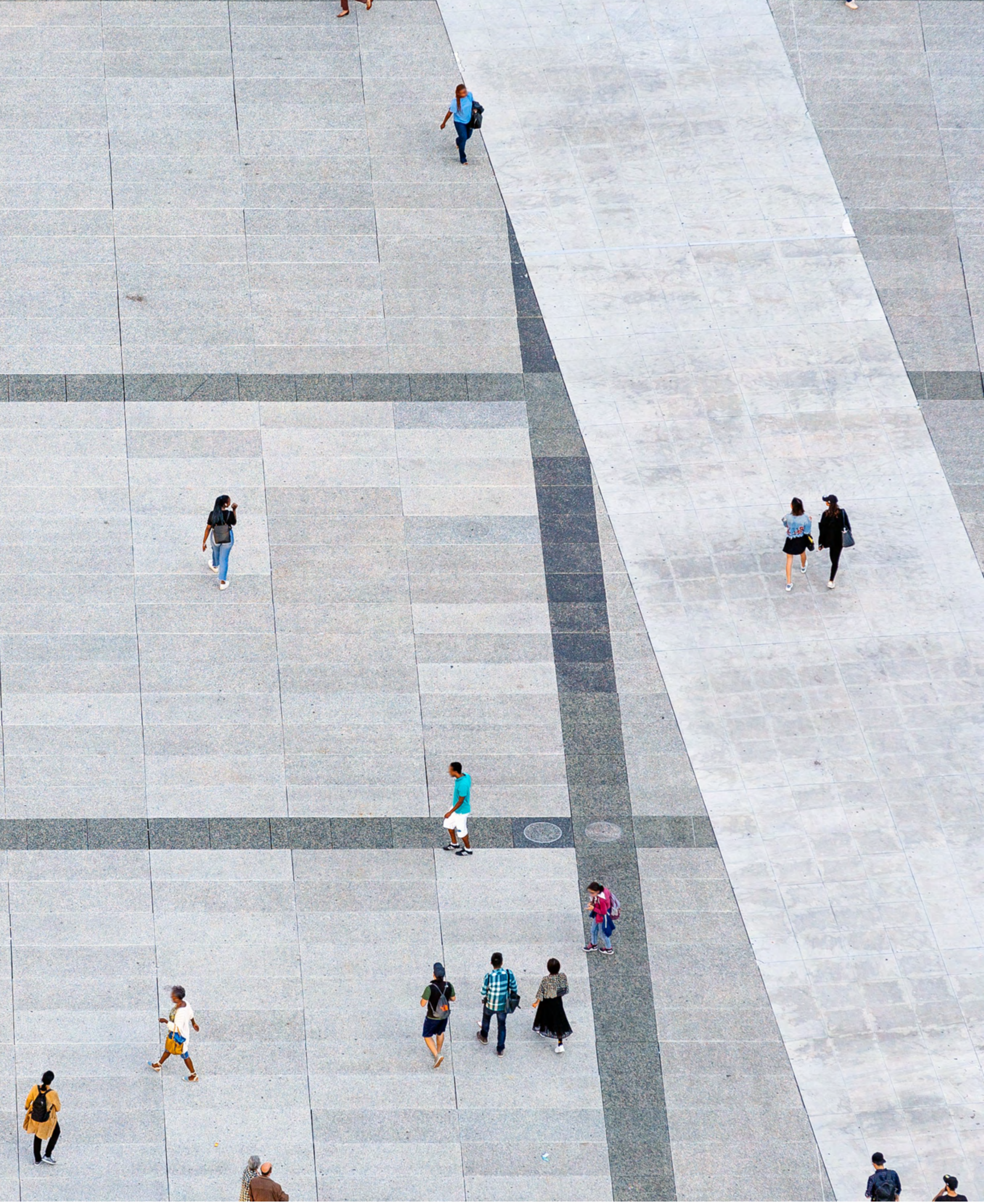
Most issues revolve around the scarcity of data and the onerous data preparation processes involved. Data scarcity is amplified especially in data-sensitive industries like finance, where data is often confidential or requires careful handling due to user privacy concerns. Yet, AI systems require massive training datasets, even more so when in deployment. While data is already scarce, "clean" data is even scanter and extremely hard to find, as data also often comes from a wide array of sources in a multitude of forms and formats, some more appropriate for usage than others. Hence, data must be “cleansed” for actual usage to provide high-quality data for proper training of the AI model and prevent potential bias due to skewed data. The data also requires proper annotation or labelling for the supervised training of the AI model. This results in massive amounts of manpower and time required to both cleanse and annotate data.

In contrast to the large volumes of data required to move into deployment, it is easy to see why many firms struggle with tackling the data issue in trying to bring their AI solutions to deployment.

MYRIAD OF UNANTICIPATED TECH HICCUPS

Lastly, scaling up brings about many unexpected issues and difficulties. As AI models and solutions grow in terms of their uses and applications, they would inevitably become more interconnected and complex. Beyond that, as time passes, AI systems will continue to evolve even in production, in response to new trends and insights from data, updating themselves. Inevitably, new, unforeseen issues would emerge from said complexity and evolution of the AI system. While such unintended complications can always be flushed out in soft launches or pilot runs as well as anticipated beforehand, it is impossible to account for every single hitch or snag that may occur during deployment.

And in the real world, any small hitch or snag could have big implications. Be it in the front-office facing demanding customers and business users or the back office where vital operations are carried out, complications are likely to affect business operations significantly, be it in cost, reputation or efficiency. The examples are numerous, from Amazon as mentioned earlier to Google Photos and Microsoft’s Twitter bot (Buolamwini and Gebru, 2018).



Enterprise Risk

BATTERED BY UNMET ROI

Most often, the failure of AI solutions can be attributed to the failure to achieve a Return-On-Investment (ROI) satisfactory enough for the decision-makers of the business. However, beyond the technical factors mentioned earlier, the inability to achieve an adequate ROI could be due to several other reasons on the business front.

An Accenture study found that 52% of companies were unable to scale up due to an insufficient expected ROI. This inability to scale up could result in POCs being constantly abandoned and never put into production due to insufficient expected ROI as shown above, which in itself is already reducing ROI greatly because of the inability to scale up, perpetuating a vicious cycle. This is exemplified in the same Accenture study where companies who were able to scale PoCs successfully saw 86% return on investment (ROI) as compared to the 32% ROI seen by companies still stuck in the PoC stage. Considering how a large majority of companies (over 80%) are still mired in the PoC trap and constantly pushing out vanity projects with no tangible results to show for it, this is a critical issue.

Decision -making risk

TEAM ACCOUNTABILITY AND DECISION-MAKING

Furthermore, it could contribute to a heightened perception of risk which consequently hinders the actual decision-making process for purchasing decisions or implementation of AI projects. Often, in making such decisions for purchasing or implementation, it is not whether the technology is sound enough, but whether someone is willing to vouch for and take ownership of the project and its future results. Given that the upside goes to the business and the downside is borne by the decision-maker, it is certain that ROI expectations will be even higher to account for or insure against said decision-making risk. Accordingly, more AI projects would fail to scale up or delve into deployment due to insufficient expected ROI.

RESISTANCE TO AI IMPLEMENTATION

Another common element, perhaps the most important one, would be organisational or cultural resistance to the implementation of AI solutions. Such resistance can present itself at all stages of the hierarchy or business chain - from the C-suite to the run-of-the-mill employee, or even out-of-sync mindsets between top and bottom, or just a general lack of a culture of innovation.

The likeliest resistance will come from the employees and people of the business. The presence of AI solutions will definitely disrupt the work of many stakeholders, leading to great inconvenience if proper preparation is not conducted. It's important to note that preparation for the implementation of AI goes beyond just user training and technology integration. It extends to various other forms of business support, be it updating rules and policies, or amending current business processes to be more efficient and friendlier towards the integration of AI solutions. Perhaps most important is the need to maintain and boost the morale of employees, especially with the current prevalent stereotype that AI replaces human workers. Understandably, asking employees to train, program or use AI bots and solutions that could potentially replace them in the future will have tremendous implications for morale and productivity in offices. Ergo, unless a business prepares its people for the introduction of AI, it is unlikely to gain traction with a lack of buy-in by the various stakeholders, leading to a failure to scale. Yet, businesses continually fail to recognise the equal importance of organisational challenges as compared to technical difficulties.

"Yet, recent research on AI is more focused on a technological understanding of AI adoption than identifying the organizational challenges associated with its implementation (Alsheibani et al., 2020). While some studies have identified research gaps (Dwivedi et al., 2019), and looked at important aspects of being able to leverage AI technologies (Mikalef & Gupta, 2021), there is still a lack of a holistic understanding of how AI is adopted and used in organisations, and what are the main value-generating mechanisms."

In fact, in an Accenture survey of executives seeking the top challenges for scaling AI, employee adoption (53%) ranked the highest. Not far behind was an inability to set up an organisational structure for continuous innovation (48%), a lack of culture for change (43%), and a poor understanding of AI potential within top management (42%).

EXECUTIVES SEEKING THE TOP CHALLENGES FOR SCALING AI

53%

Employee adoption

48%

Inability to set up an organisational structure for continuous innovation

43%

A lack of culture for change

ALIGNMENT: WHERE BUSINESS STRATEGY AND REALITY COLLIDE

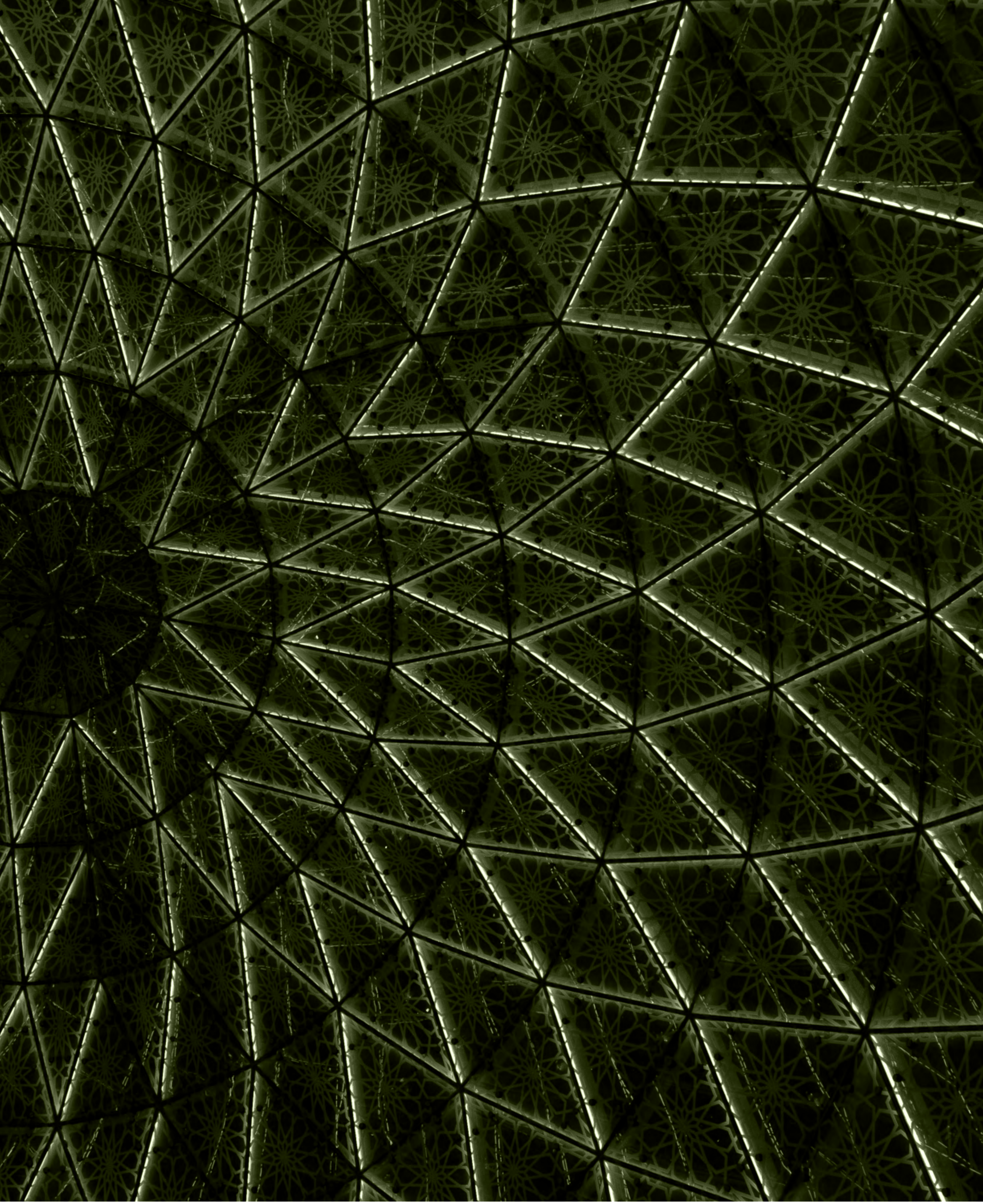
All these could be due to a poor alignment of mindsets and expectations towards AI between the business leadership and the actual subject matter experts like the technology and innovation teams. While business leadership may be influenced by idealistic strategic intent embellished by the people around them, the actual innovation leads are faced with the more grounded realities of working with and implementing AI. Faced with executives' over-ambitious strategic goals, innovation teams on the ground will inevitably face difficulty in living up to these goals, resulting in potential conflict. Henceforth, a split in the alignment of strategy and reality can occur, resulting in misguided expectations, leading to the perceived failure and inevitable axe of said AI projects.

Difficulties in encouraging innovation can also occur in poor structures or hierarchies within the business. In an attempt to mitigate the earlier mentioned misalignment of mindsets between executive and employee, businesses may often attempt to centralise innovation strategy and implementation to get everyone on the same page about AI. Yet, the dictation of AI implementation often results in a lack of buy-in by the different users and stakeholders across the business and stifles innovation. Conversely, decentralisation results in numerous isolated, uncoordinated silos with their own AI solutions and strategies, limiting the potential to scale and reap the benefits of AI.

Misalignment in mindsets can also occur in the failure to measure or estimate any bottom-line impact or benefit from these AI investments, potentially leading to an underwhelming ROI as mentioned above. Often, despite the millions of dollars invested in such AI projects, companies fail to attribute any impact to these investments due to the neglect of proper metrics and their estimation. These “guesstimates” both apply before and after the implementation of AI. Before, businesses would recklessly implement AI solutions without precise and particular consideration of business value and feasibility. Without a proper strategy, businesses approach AI in a ragtag and generalised manner, in the mistaken belief that applying AI in a blanket fashion will somehow generate benefits and patch up loopholes everywhere. This is not sustainable and will result in ineffective or unmeasurable AI solutions. In the wake of the ragtag application of the AI solution, businesses often fail to recognise what exact impact it had, considering the latter’s multifaceted nature cutting across a multitude of systems and processes, losing sight of many second-order impacts and beyond. PwC’s 2022 AI Business survey found approaching AI in an coordinated manner directed by strategy as compared to approaching AI in a piecemeal fashion resulted in almost double the success rate of widespread AI adoption and the achievement of substantial value from AI initiatives. All in all, this will inescapably result in the failure to scale up AI projects, then resulting in reduced confidence and trust in the transformational capabilities of AI within the business. This kickstarts and perpetuates a vicious cycle which reduces the appetite for innovation within the business, hence resulting in a lack of a culture of change.

It is clear then, that despite executives’ eagerness to jump into technical development and kickstart the “automation revolution”, without proper consideration, preparation and selection on the business front, numerous problems will emerge in the implementation and scaling of AI solutions as well.

How, then, can we solve this?



Technological Solutions

The most essential step that businesses need to take is to adopt the general, overarching mindset of generalisability and flexibility in adopting and implementing AI. Businesses should aim for scalability and flexibility in all aspects and stages of their development processes, from data to models.

MODEL DEVELOPMENT

The first step of the AI process is model development. As businesses start to develop AI solutions for use, they should aim to develop general models that can be applied to a wide variety of fields or aspects of the business. Techniques like transfer learning can then be utilised to scale these models across domains by delineating them for specific tasks. In this case with simple retraining or easy swapping of models, models can be reused instead of having to repeatedly build fixed and separate models from the ground up, saving extensive amounts of time and effort. Optimally, businesses can compile and maintain common frameworks for setting up AI solutions and models. This extends beyond just algorithms and models - common development practices and pipelines are also reusable and can be iterated in the scaling of AI across the business, as multiple solutions and models are built for different applications across the business. This not only saves time through the streamlining of development but also improves quality as building a new AI solution each time is no longer a novel process starting from scratch but a familiar protocol that is standardised and checked for quality already. After all, would you manufacture v component of its product from scratch with every order, without any standardised or consistent parts, processes, and quality-assurance protocols? Then why do the same for AI, working manually without enterprise mechanisms, exposing yourself to huge inefficiencies and risks?

For example, Nexus FrontierTech uses Podder, a repository of various processes, practices, tools and frameworks to aid enterprise scalability of AI. Such processes and practices include iterative development practices, reusable development pipelines, extensible AI-aware system architectures, common frameworks and interoperability standards. The usage of these reusable assets and components provides an immediate base for new AI projects to build upon, making the delivery process much quicker and simplifying it as well.

THE IMPORTANCE OF DATA IN MACHINE LEARNING

The second step of the AI process is having to train or retrain the AI model, for which data, lots of it, is essential. Yet, Andrew Ng, founder of deeplearning.ai, Coursera and the Google Brain Project, claims:

> *"Even if you only had small data, it is almost always a terrible idea to wait for more data before developing ML solutions in an enterprise."*

Data can be sourced not just internally, but from various external sources as well. A multitude of datasets is available, from training datasets on Kaggle to plain publicly available data online. An example of the latter could be public financial statements from listed companies or crowdsourcing data from the billions of online interactions every day, all depending on what you intend to develop.

In certain industries, where one is dealing with sensitive information like personal data or financials, data masking can be utilised to make data usable yet secure simultaneously. Various techniques exist from binary substitution to complex encryption, all of which will ensure proper data security and governance, while allowing for much more high-quality and relevant data for model training and development. Beyond that, data can also be reused and recombined across a variety of applications. As businesses conduct more and more AI projects, they will amass more and more labelled/curated datasets. With proper storage, firms can build on this past "knowledge" gained by utilising past data for present tasks if the tasks are similar to the initial purpose of past tasks. Just like the models mentioned earlier, data can also be reused and repurposed to overcome data scarcity and collection challenges. Accordingly, businesses must develop and institutionalise scalable management of data with proper data collection and storage. This goes hand-in-hand with scalable oversight, which "encompasses methods that reduce the time, cost, errors, and labour required to collect and curate datasets."

Granted, while it is extremely difficult, or even no way around the tedious data labelling process for supervised learning, quality data engineering, together with the methods mentioned above, can mitigate the pains of data labelling and annotation. Businesses should aim to have clear and concise data pipelines with:

1. clear collection from a variety of data sources, be it AWS S3 bucket, computer, or internal database like MongoDB
2. Specific queries/data gathering from databases
3. Appropriate data storage be it in data lakes or warehouses

Businesses will differ in their data schema or pipelines, ETL[1] or ELT[2], and there is no one-size-fits-all approach when it comes to data considering the different engineering priorities that each business has. Regardless, the crux of the issue is for businesses to get their data engineering in order, ensuring that schema is carefully outlined with clear flows and precise standards.

If one lacks data, one can make data! Businesses have numerous options to increase the data they have, from advanced techniques like Generative Adversarial Networks (GANs) to plain and simple data augmentation by taking one dataset and recreating 10 different versions of it.

---

[1] Extract, Transform, Load

[2] Extract, Load, Transform

For example, this image of a cat could have 10 twins!

B&W, skewed, rotated etc.

By simple data augmentation and thinking out of the box, datasets can multiply tenfold, exposing the algorithm to a much larger array of data and giving it greater capabilities in recognising different data formats or types.

Large datasets aren't even needed before implementing the AI solution - With the Human-In-The-Loop (HITL) approach, AI solutions can continue to improve after implementation with their human operator continually grading and correcting their output. This creation of a continuous feedback loop between humans and machines creates a continuous circle where Machine Learning algorithms are trained, tested, tuned, and validated, learning "on the job" to improve and refine its logic and results. For instance, Nexus FrontierTech's AI Factory utilises HITL in the process of building the AI pilot programme and helps you achieve reasonable results even with a small or insufficient data set.

DESIGN AND EXECUTION OF MLOPS

The third step involves bringing all of these concepts to life, of which the key lies in the proper design and execution of Machine Learning Operations (MLOps).

First off: What is MLOps? Any introduction must start off with its predecessor, DevOps, an amalgamation of the concepts of Development and Operations. DevOps involves a set of best practices and mindsets derived from Agile software development and implementation to streamline both software development and deployment, "increasing an organisation's ability to deliver applications and services at high velocity: evolving and improving products at a faster pace… "

Such best practices include a CI/CD pipeline (Continuous Integration/Continuous Delivery), constant monitoring and tracking, continuous collaboration via feedback loops, InfrastructureAsCode (IAC), as well as a microservices architecture. These practices then support the iterative development practices and reusable development pipelines that we earlier mentioned, allowing for the smooth and easy scaling of software solutions within the business. MLOps then is an AI-specific interpretation of DevOps. Analogous to DevOps, MLOps involves a set of best practices and mindsets to streamline both AI development and deployment, increasing an organisation's ability to deliver AI solutions into production by creating a "AI Factory" capable of achieving scale as well. MLOps also includes the same practices that DevOps has, applied in an AI context - Models will be constantly monitored and tracked while receiving incremental improvements via feedback loops between user and engineer (more on that later).

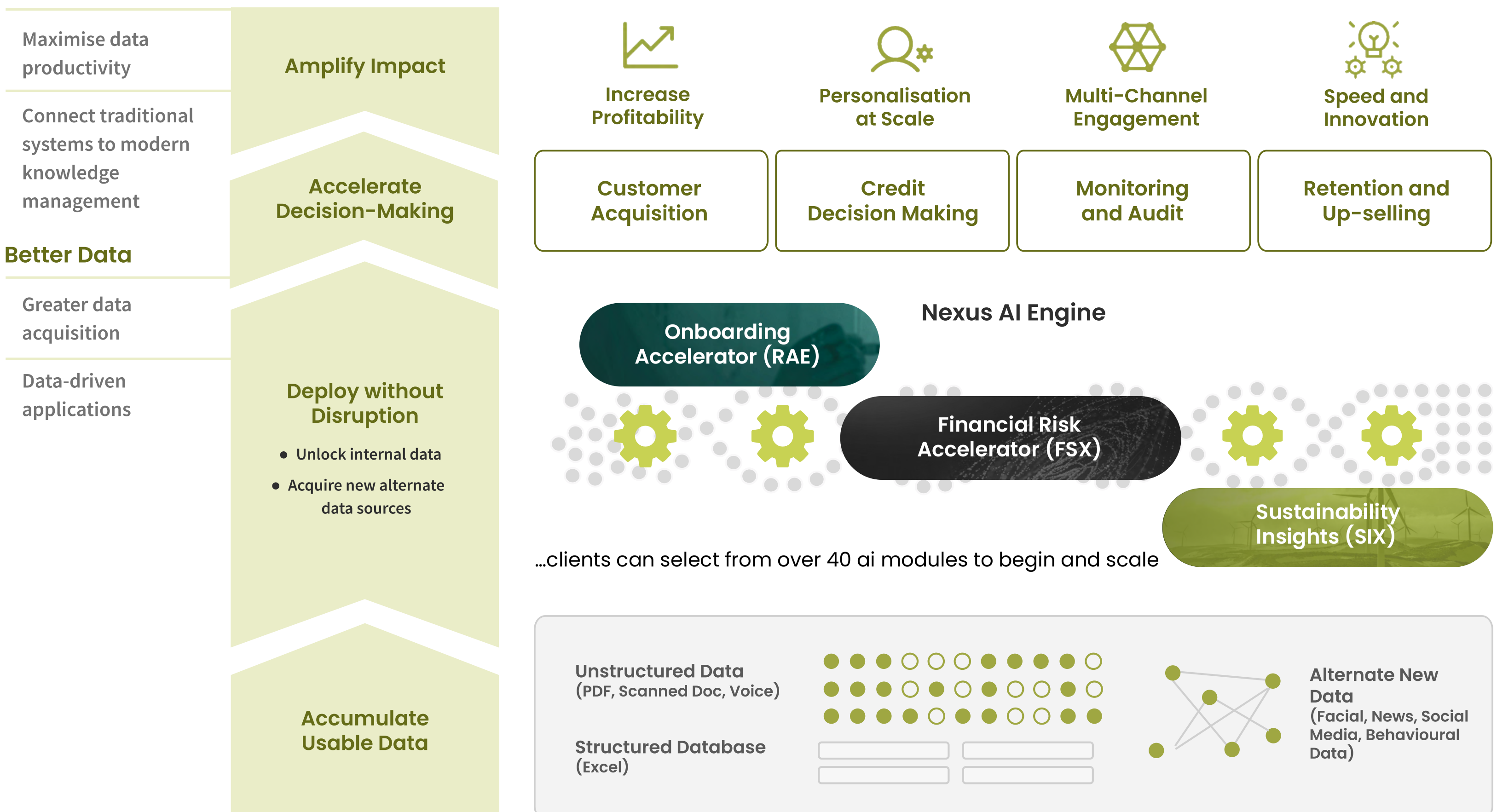
For instance, CI/CD pipelines now involve not just the models, but the data schemas and the data itself that the model is reliant on. Continuous Integration now becomes more than just infrastructural integration, but integration with the latest data that is coming in live and direct, to keep the model updated and relevant; necessarily, CT (Continuous Testing) also becomes a third component of the pipeline, where models are constantly retrained and tested with the aforementioned new data. And the latter could be facilitated by a system architecture which allows for easy switching of models for retraining and retesting in the case of redundancy or rollback, which goes to show how MLOps expands beyond just the models' development and deployment themselves to the entire AI solutions stack. From the repository to maintain and manage AI models to the Docker containers, mtypically coordinated and managed together by Google Kubernetes or Amazon ECS, MLOps is essential in every aspect and area.

The easy switching of models, streamlining of processes and utilisation of reusable assets and components that are checked frequently for quality gives one vital advantage - speed. When engineers have to build from scratch, executives often complain it takes up to more than a year to implement potential AI solutions. Contrast that with organisations that employ MLOps, where engineers focus on only assembling things together, where AI solutions can be implemented within 2 to 12 weeks with minimal cost and effort. These reusable assets range from common standards and pipelines as mentioned earlier, or "ready-to-use" products needed for a particular function eg. unifying a specific set of data.

To illustrate,
Nexus FrontierTech is a strong proponent of MLOps and Nexus' proprietary AI platform, Podder, adopts MLOps by handling Testing, Packaging, CI/CD, Diagnostics and scalability.

Nexus Value Proposition

Nexus is modernising TradFin with *modular AI engine* to amplify its’ impact way faster



Moreover, the continuous monitoring and efficacy testing of models that are integrated into a system ensures AI solutions are always functional and useful. McKinsey found that traditional businesses stop using nearly 80% of their AI solutions despite extensive investment, because they no longer provide value and there's no immediate solution or even understanding as to why. In contrast, companies adopting MLOps shelve 30% fewer models and increase the value they realise from their AI work by as much as 60%. If businesses adopt MLOps and carry it out properly, it allows for faster and higher quality development and deployment of AI solutions. More importantly, MLOps can aid in the scalability of thousands of AI models and reproducibility of pipelines through proper management and oversight, with continuous integration, development and testing.

McKinsey's Global Survey on AI in 2021 found:

"The companies seeing the biggest bottom-line impact from AI adoption (at least 20% of EBIT) are more likely to follow both core and advanced AI best practices, including MLOps…"

The occurrence of unexpected issues, which we highlighted just now, can also be mitigated by MLOps as well. In the first place, the stronger scrutiny and more regular reviewing that takes place in feedback loops and continuous testing will help to curb model drift, bias or any other issues that may occur. In the case some small flaws slip through, they can be easily mitigated with the fast swapping of models that a fluid system architecture allows for, as well as effortlessly diagnosed and remedied thanks to the greater transparency and oversight that MLOps affords. Proper MLOps would also ensure there is appropriate contingency planning for redundancy or updates to ensure everything runs smoothly; in the case it doesn't, every complication has its solution.

LEVERAGE CLOUD COMPUTING FOR AN AGILE MODEL

Lastly, companies can leverage the cloud. Granted, this may not be possible for some businesses who have their hands bound due to the need for compliance with privacy regulations. Or businesses could have valid security concerns - After all, hosting it in your own secure data centre will always be safer than leaving it in the public eye vulnerable to attacks from any and everybody. Nevertheless, businesses can mitigate against this with adequate guidelines and policies. At the end of the day, it is not system gaps, but human error, that causes 85% of all data breaches. And if businesses get cloud security correct, the rewards to be reaped are tremendous. First and foremost, the cloud affords great agility and flexibility to businesses. Cloud environments allow for quick and seamless utilisation of the common and reusable frameworks, pipelines and models that were earlier mentioned. It also becomes easier to keep up with technological advancements - as per the CI/CD/CT pipeline, old models can be simply swapped out to be retrained or even for new ones with new capabilities, scaling up the entire presence of AI within the business. The same McKinsey's Global Survey on AI discovered:

"The high performers use cloud infrastructure much more than their peers do: 64 percent of their AI workloads run on public or hybrid cloud, compared with 44 percent at other companies. This group is also accessing a wider range of AI capabilities and techniques on a public cloud. For example, they are twice as likely as the rest to say they tap the cloud for natural-language-speech understanding and facial-recognition capabilities."

Ideally, businesses should aim for data, AI and cloud as a unified whole - a PwC study found:

"AI can deliver more value at scale when it's embedded in application systems that work nonstop, analyzing and acting on data from inside and outside the organization. These systems, in turn, need cloud-based computing power that can scale up and down to help meet demands."

This brings us to the second key advantage of cloud computing: Computing Power. Cloud is significantly more efficient and less resource-intensive than maintaining your own data centres. As mentioned earlier, when businesses scale their AI solutions, their computing requirements will increase exponentially, posing immense requirements be it in terms of cost, storage et cetera. Cloud goes a long way to mitigate these issues by offering a more affordable and feasible option by doing away with the need to purchase, build and maintain expensive specialised hardware in large data centres. Furthermore, the cloud also offers flexibility in ramping up computing resources as and when needed. This aids scalability for businesses, which can now retrain and operate models as and when necessary without having to worry about limitations. For instance, Amazon's EC2 instances allow for auto-scaling for high-performance computing (HPC) applications like AI models. Seamlessly scaling up and down depending on the computing demand allows for peak performance and maximum cost-efficiency at the same time.

Organisational Solutions

Beyond technical solutions, business strategies could prove the answer to scaling up AI as well. Businesses often overly fixate on technological implementation instead of organisational implementation. A study by Monash University found:

“Furthermore, most recent AI studies at the organisational level have tended to concentrate only on a technological understanding of AI adoption rather than identifying the strategic and business leader challenges associated with its implementation.”

This is in spite of organisational challenges hurting the most when it comes to the implementation of AI.

These challenges span the entire length and breadth of the business, from the employee to the C-suite at the very top. The C-Suite matters the most in ensuring the scalability of their AI solutions, holding various responsibilities. At the very fundamental level, executives have to educate themselves and buy into the potential of AI to bring their business to the next level.
After educating themselves, executives have to ask themselves:

1. What threats do AI and other related new technologies pose to the company?
2. What opportunities do AI and other related new technologies offer to the company?

It is essential that executives answer this question honestly and thoroughly to determine and articulate their beliefs about AI, to understand their true feelings about AI. If said feelings were negative and only repressed so as to keep up with the Joneses, the implementation of AI would immediately be hampered and most likely, fail. After all, belief is always essential in the performance of any deed.

Indeed, one of the strongest determinants of AI adoption is support from top management. Executive support is critical in conquering both technological and organisational difficulties. These difficulties can range from funding and resourcing issues to inertia generated by company culture. A McKinsey survey found successful AI adopters rated C-suite support two times of companies who hadn’t successfully adopted AI, with the aforementioned support branching out to every C-level officer as well as the board of directors.

If said belief or feeling is positive with regards to AI, then the next course of action for executives would be to plan out a grand strategy for the implementation of AI within the company. First and foremost, executives must understand and know what they want to achieve with AI, which should align with the business’ existing goals. Then, businesses must conduct a pragmatic and objective analysis of every pain point present, and then examine the potential solutions AI can offer to address these pain points in a realistic and sensible context. This includes a real-world overview of the AI solution’s capabilities and limitations, and a cost-benefit analysis of whether the AI solution is worth the investment. Unfortunately, this is the step that most businesses get wrong. Instead of focusing on their problems and letting AI work for them to solve these problems, businesses often “work” for AI instead; distracted by the hype and buzz around AI, they focus on chasing the latest AI trends or on the flashiest AI technologies which are hardly applicable and relevant to their needs, and hence are doomed to fail or never be scaled up for further use.

Instead, businesses should configure their desired goal from using AI based on their issues and needs. This will form the grand strategy that will be the guiding principle that sets the course of deployment and scaling of AI within the business, an amalgam of quick efficiency gains and a long-term route to scaling up AI, solely focused on greatly improving productivity and potential. This strategy is certain to disrupt business processes, structures and cultures as it demands data-oriented change, but it is crucial that executives push through as sustained commitment is key to long-term success. Thereafter, businesses should develop an AI portfolio that encompasses every potential AI solution, each qualified and prioritised according to the business value it can bring and its alignment to the business’ AI strategy as mentioned earlier. This portfolio of ideas can be constantly shaped and developed as both technology and business needs evolve, assessed not only based on business value, but crucially the alignment to the business’ AI strategy as well to determine the extent to which the AI solution can be scaled across the enterprise.

By stepping back and creating a reservoir of AI ideas instead of diving right into testing and implementation of solutions, it allows the business to carefully visualise the benefits and limitations of these potential solutions, allowing for quick qualification, accelerated approval and speedy production, but at the same time, in case the solution doesn’t work out, businesses can swiftly shelve the solution with minimal cost and effort.

CASE STUDY

The Nexus AI Factory

When a UK government agency faced issues in prioritising use cases for AI automation of their manual processes, Nexus FrontierTech aided via setting up an “AI Factory”. Nexus’ AI Factory is a production programme to identify, prioritise and execute pilot projects systematically and quickly.

Nexus consultants utilised both business use case analysis and technical feasibility assessments to parse through and qualify over 100 use cases, pushing a select few into the development phase. Nexus’ holistic approach ensured that those use cases pushed into development were aligned with the AI strategy of said agency and addressed the key areas of need as well. Ultimately, the agency saw an acceleration of their operational processes by 60% within 3 months. Moreover, Nexus also conducted leadership training sessions to educate executives on AI and left the agency with a reusable framework for proper qualification of AI use cases and execution of AI initiatives in the future. Overall, using AI Factory, the UK government agency accelerated their operational process by 60% within 3 months.

Download the full Case Study

or visit https://nexusfrontier.tech/resources/transforming-operational-processes-using-nexuss-ai-factory/

AN AI PLAYBOOK

Hand in hand with the portfolio of AI solutions is a playbook with the various steps and guidelines for implementation and deployment of AI. Simply expressed, the portfolio acts as a repository for every AI solution, while the playbook acts as a guide for the implementation of those selected solutions, jointly forming an "AI pipeline" within the business to swiftly produce and scale AI solutions to solve the business' ailments.

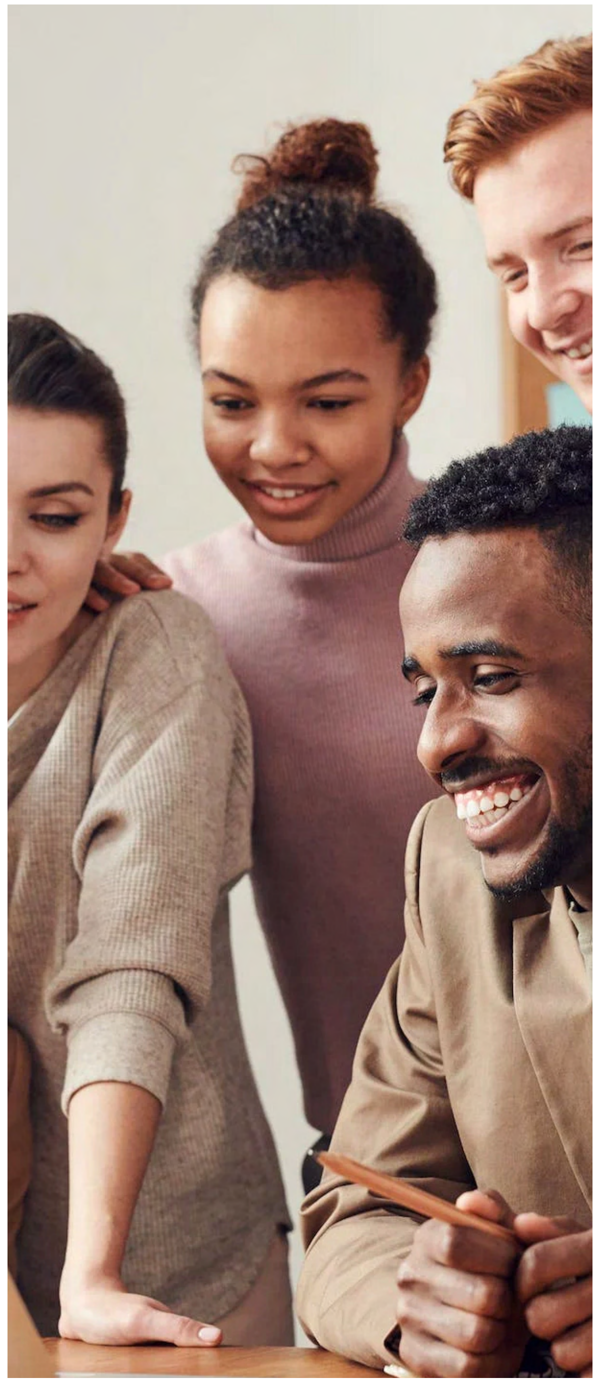
This AI playbook should follow the entire lifecycle of said AI solution, from idea to Proof-Of-Concept to production to scaling, and cover every aspect of the process of AI implementation. Once done and refined multiple times over several iterations of AI deployment, businesses would be able to expertly deliver AI solutions with minimal effort and complications, aiding the business' ability to scale and become a truly AI-powered organisation. A good AI playbook should have various key principles, for example a strong data foundation where supporting digital assets and capabilities like a data ecosystem as mentioned earlier are present. With a proper AI strategy and playbook, businesses are much better equipped to master the challenge of scaling up AI. In fact, Accenture found that 71% of businesses successful in scaling up had a clearly defined strategy and operating model.

In addition, businesses should clearly define the KPIs / metrics to indicate the level of success in achieving the goal as outlined in the AI strategy, as well as the plans and timeframes for doing so. Deciding which KPIs could be difficult - while many use quantitative AI metrics like accuracy rate which are excellent indicators of model performance, they often fail in indicating project success. While businesses tend to obsess over achieving 100% accuracy rates, they often fail to ignore various other factors like time, cost, effort, features and workflow all of which are critical in determining the success of a certain AI solution in production and scaling. Hence, organisational-focused KPIs could become more valuable as they are able to measure the impact the AI solution has on the business. However, such KPIs are also harder to quantify, which could hinder the actual insights it could bring. Nevertheless, the crux of the issue still remains that businesses define an established way of measuring value and ROI improvements.

Organisational measures for improving the scaling potential of AI extend to the rest of the business as well. Businesses can start with restructuring prevailing organisational arrangements. Many businesses are often siloed physically or mentally, which severely restricts the collaboration needed for MLOps. Consider a traditional silo-ed business where technical experts and business experts are separated without communication or collaboration. AI solutions brought in by the technical unit would be irrelevant and ineffective to the end-user, the business unit, while AI solutions brought in by the business unit would be technically unfeasible and doomed to failure. In the implementation of AI solutions, be it starting off with a PoC or maturing via scaling, a diverse team is required with both technological practitioners and end-users to optimise the approach and development of AI. This is what facilitates the "feedback loops" between end-users and engineers as mentioned above in the CI/CD pipeline and continuous testing to ensure AI solutions remain relevant and effective. Beyond just enhancing and refining solutions, diverse teams allow for long-term benefit as well through the exchange of traditionally sector-specific technical expertise. By establishing interdisciplinary teams with various skill sets in the implementation and scaling of AI, developers and engineers better understand end-users' value chains, while business units better understand the feasibility and potential of various AI solutions: what is possible and what is not. With better collaboration, this allows for not just more relevant solutions when scaling to different business units within the organisation, but also solutions that have more potential to scale when starting off as a PoC or during initial implementation as all the various stakeholders have been consulted and considered in design and decision-making.

Granted, this is easier said than done. Businesses have to consider carefully how to best set up these interdisciplinary teams in order to establish the right connections while not disrupting current processes as much as possible. Businesses also have to gingerly navigate the tightrope between the centralised model which allows for standardisation but restricts innovation and the distributed model which allows for autonomy but also causes disorganised discrepancies within the entire business. One important measure that could go a long way to address such issues would be bringing in a "translator manager" to fill in the gap between decision-makers, engineers and end-users.

These translator managers act as both an intermediary for communication between various stakeholders by "translating" each stakeholder's needs to each other, and as a manager overseeing the project while generating buy-in and support for further scaling across the organisation. Ideally, they should possess a unique talent mix of both business nous and technical know-how together with project management experience so as to properly oversee every facet of the implementation and scaling of the AI solution. Some examples of similar roles already put in place include project managers or solution architects.



Collaborative partnerships with Nexus FrontierTech

Nexus FrontierTech places a huge emphasis on stakeholder engagement and education via clear and frequent communication. Nexus adopts 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 the creation of feedback loops via frequent user interviews and sit-ins on client calls and presentation to both understand end-users' needs and continually improve the AI solution. Any issues were addressed via frequently sharing log files generated from model processing and output, sending screenshots, and discussing updates and issues on calls to allow for broader and deeper visualisation of the issues at hand. Nexus also appoints project managers as well as solution architects to bridge the gap between business end-users and technical teams by translating each side's needs and difficulties, with the former overseeing the implementation of the AI solution as well.

SOLVING THE LAST MILE PROBLEM

However, as much as businesses can develop brilliant and revolutionary AI solutions, it is all for nought if businesses can't overcome the "last mile" problem of ensuring the insights provided by AI are instantiated in both practices and processes. Simply put, what use is a solution if no one is willing to use it?

To address this issue, businesses now need to focus on the intangible: The development of a culture welcoming and enthusiastic towards the usage of AI. This comes in 3 different aspects, arranged in increasing order of difficulty:

1. Ensuring organisational readiness
2. Fostering open-mindedness and bias towards innovation
3. Addressing employees' concerns and reassuring them

1 Ensuring organisational readiness

Firstly, businesses must ensure that their employees are suitably equipped with the skillset to work with their new AI tools and solutions. Employees' technical skills should be properly evaluated to determine the level of technical expertise within the organisation; be it in the usage of AI libraries like TensorFlow or the visualisation of workflows and logic of existing business processes and the consequent application of AI solutions to them. If said expertise is lacking, then upskilling will be essential in making the organisation "digital-savvy" enough for successful implementation and scaling of AI systems. Needless to say, technical knowledge and domain expertise will be needed in abundance to deploy AI systems effectively and scale them, and it is essential that an organisation prepares its people well enough to develop, utilise and expand its AI capabilities.

2 Fostering open-mindedness and bias towards innovation

Secondly, businesses must instil an innovative culture within their organisation. A culture of innovation would produce more creative and beneficial AI solutions, as well as make adoption of AI solutions easier and smoother, which is backed up by various studies that have found company culture to have a direct impact on the adoption of AI. After all, an innovative mindset goes hand-in-hand with AI, an innovative technology, and thus is cited to increase employees' support and openness towards the deployment and use of AI technologies. As Patrick Mikalef and Manjul Gupta concluded,

"Therefore, organisations with an innovative culture are posited to be better positioned to integrate AI in their work line."

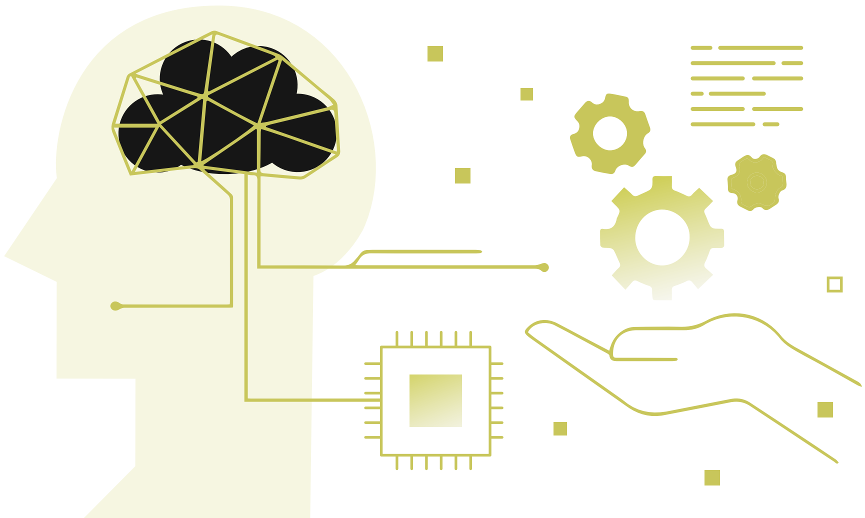
3 Addressing employees' concerns and reassuring them

Last but not least, perhaps the most difficult is the need to allay employees' concerns and address them so as to gain their trust towards their new AI tools and technologies. Employees' concerns towards AI are often borne out in two different ways - Concerns over working with their future replacements, and a lack of trust towards AI.

The former involves a 180 degree change of entrenched mindsets strengthened by years of prevailing perceptions of AI as the ultimate villain who will be responsible for taking over millions of jobs and becoming our overlords à la The Terminator. To counter this perception and change this mindset, businesses need to make fundamental changes to prevailing expectations about "work" while at the same time further empowering employees.

To start things off, businesses need to make the role of AI clear to their employees, and signal the shift from "workforce" planning to "work" planning. An Accenture survey found that 78% of companies successful in scaling AI fully understood it and how it applies to their role, compared to 59% of other companies. Beyond that, a clear demarcation between man and machine must be made, while at the same time always adjusting it in preparation for new markets, products, technologies and roles. This demarcation is made by empowering employees to take control over their AI tools and solutions instead of running them centrally. Granted, roles must be redesigned or even invented, and employees must be trained (the upskilling mentioned earlier). But by decentralising these AI solutions and delegating authority over them to employees, it allows for an immense cultural transformation which will see increases in employee engagement and participation through a greater sense of empowerment and ownership. To boot, delegating authority over AI solutions to employees allows for a much larger and more relevant pool of feedback for the earlier mentioned "feedback loops", enabling continuous improvement.

INSIGHT



The Human-In-The-Loop Strategy

Nexus is a strong proponent of the "Human-In-The-Loop" concept, internally referred to as our "eXpert-In-The-Loop" approach, a process that leverages both human expertise and machine efficiency in the creation and operation of AI solutions. With X-in-the-loop, no single task will be entirely completed by a machine or a human working on their own; while algorithms will continue to do their programmed tasks, humans (your employees) will have oversight over the algorithms' output and be in charge of reviewing the produced output. If the produced output is wrong, it can be corrected by the employee in charge, allowing for further improvements and refining of the algorithm, improving the accuracy in the long-term.

This results in "collaborative intelligence", where machines take charge of manual, laborious, repetitive tasks, while employees retain decision-making control, working in tandem to do better than an independent machine or human. Beyond accuracy, the XITL approach also has several other advantages:

1. **Empowers employees through the delegation of control (as previously mentioned)**
2. **Mitigates the "small data" issue (as previously mentioned)**
3. **Increases transparency by adding a human into the workflow (which will be touched upon later).**

SOLVING THE LAST MILE PROBLEM

Trust is a key enabler to ensure the smooth integration of AI into business processes and hence it is essential that it be cultivated. As AI develops and matures, they often expand into tasks that replicate human cognition or automate previously manual tasks. And while we mentioned above that employees can be owners and operators of AI tools that did the tasks they were previously responsible for, so as to empower them, they still need to be able to trust these AI tools so as to rely on their insights and even decisions. This is much harder than it looks: While one can take some time to trust a new co-worker or team member, trusting a machine is a whole different ballgame. Research has found that the lack of emotions and empathy on the part of AI could act as a severe limiter and complication in the interaction between humans and AI, making the process of building trust very arduous. Hence, the lack of trust between employees and AI could act as a severe barrier in the utilisation of AI solutions.

So how do we develop employee-AI trust? Studies have shown that a lack of transparency breeds employee distrust towards AI, comparatively, by demonstrating their inner logic and processes behind how AI solutions work, and their inbuilt standards of safety and reliability, trust towards AI has risen considerably. Hence it is essential that businesses take the time to understand and demonstrate to all involved stakeholders how the AI solution works and why the AI solution is needed. This can be facilitated by adopting explainable "glass-box" AI where its workings and conclusions are visible to all, in addition to third-party audits and checks of the code and setup of these AI solutions. Responsible AI governance and ethical considerations should be placed at the very core when designing AI solutions. Businesses can also adopt the abovementioned HITL approach to add a human into the workflow, allowing for better visualisation of how AI solutions make decisions and arrive at their conclusions. All these measures act as reassurance to end-users and various other stakeholders that these ML algorithms derive their conclusions fairly, reasonable and reliably. As this understanding is built, trust will follow, and it is more likely that your AI solution can get off the ground and expand throughout the organisation as understanding and trust continues to grow.

Conclusion

Few successfully implement AI. Even fewer successfully scale AI. But it doesn't have to be this way. Despite the seemingly numerous and uncompromising challenges present in scaling AI in your business, there are ways to circumvent and overcome these challenges. Both technical and organisational measures play a key role in addressing these challenges, be it the implementation of MLOps or the institution of an AI strategy and culture of innovation.

Firms can also look beyond tackling these challenges on their own to the myriad of AI providers that can act as partners to help you on your AI journey. It is not needed or even desirable at times to build new proprietary solutions in-house, and businesses can take advantage of these AI providers' expertise and reusable assets to kickstart their AI journey. Many also don't realise that working with AI providers doesn't just imply purchasing an enterprise AI solution - working together also allows for the transfer of vital knowledge and value and potential as well.

Take for example, the earlier case study of Nexus' collaboration with a UK government agency, where beyond just having a one-time consultation, they received training, knowledge, frameworks that they could utilise for similar issues in the future. In fact, by just working with AI providers, businesses get to witness firsthand how they work and what best practices they employ, e.g. HITL approach, interdisciplinary collaboration, obtaining vital know-how and expertise, all of which would be needed in abundance for the journey to scale AI ahead. After all, they've been there, done that.

BIBLIOGRAPHY

Accenture. (2020). Ready Set Scale. [ebook] Accenture. Available at: <https://www.accenture.com/_acnmedia/PDF-113/Accenture-Ready-Set-Scale.pdf>.

Accenture. (2022). The Art of AI Maturity: Advancing from Practice to Performance. 1st ed. [ebook] Accenture. Available at: <https://www.accenture.com/_acnmedia/Thought-Leadership-Assets/PDF-5/Accenture-Art-of-AI-Maturity-Report.pdf>.

Accenture Research analysis of the world's 2,000 largest companies by market capitalization mentioning AI in their earnings calls. Formula is based on CEOs of companies that had earnings call in 2020, and CEO was present at the call, and CEO mentioned AI. 46% of these CEOs mentioned AI in their earnings calls, in 2021 up from ~35% in 2017.

Alsheibani, S., Messom, C., Cheung, Y. and Alhosni, M. (2020). Reimaging the Strategic Management of Artificial Intelligence: Five Recommendations for Business Leaders. AMCIS 2020 Proceedings: IS Leadership and the IT Profession. AIS Electronic Library.

Amatriain, X. and Basilico, J. (2012). Netflix Recommendations: Beyond the 5 stars (Part 1). [online] Netflix Tech Blog. Available at: <https://netflixtechblog.com/netflix-recommendations-beyond-the-5-stars-part-1-55838468f429>.

Buolamwini, J. and Gebru, T. (2018). Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification. Proceedings of Machine Learning Research, 81,pp.1-15.

Businesswire. (2022). NewVantage Partners Releases 2022 Data And AI Executive Survey. [online] Available at: <https://www.businesswire.com/news/home/20220103005036/en/NewVantage-Partners-Releases-2022-Data-And-AI-Executive-Survey>.

Clifford, C. (2018). Google CEO: A.I. is more important than fire or electricity. [online] CNBC. Available at: <https://www.cnbc.com/2018/02/01/google-ceo-sundar-pichai-ai-is-more-important-than-fire-electricity.html>.

Dastin, J. (2018). Amazon scraps secret AI recruiting tool that showed bias against women. [online] Reuters. Available at: <https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G>.

Databricks. (2022). What is MLOps? Databricks. Available at: <https://www.databricks.com/glossary/mlops>.

Davenport, T. and Bean, R. (2022). Data and AI Leadership Executive Survey 2022: Executive Summary of Findings. [ebook] NewVantage Partners. Available at: <https://c6abb8db-514c-4f5b-b5a1-fc710f1e464e.filesusr.com/ugd/e5361a_2f859f3457f24cff9b2f8a2bf54f82b7.pdf>.

Dougherty, C. (2015). Google Photos Mistakenly Labels Black People 'Gorillas'. [online] New York Times. Available at: <https://archive.nytimes.com/bits.blogs.nytimes.com/2015/07/01/google-photos-mistakenly-labels-black-people-gorillas/>.

Enholm, I., Papagiannidis, E., Mikalef, P. and Krogstie, J. (2021). Artificial Intelligence and Business Value: a Literature Review. Information Systems Frontiers.

Finextra Research. (2018). Sage CEO steps down amid cloud problems. [online] Available at: <https://www.finextra.com/newsarticle/32594/sage-ceo-steps-down-amid-cloud-problems>.

Freeman, E. (2019). What is DevOps? Amazon. Available at: <https://aws.amazon.com/devops/what-is-devops/#:~:text=DevOps%20is%20the%20combination%20of,development%20and%20infrastructure%20management%20processes>.

Glauner, P. (2020). Unlocking the power of artificial intelligence for your business. In: Innovative Technologies for Market Leadership. Future of Business and Finance. Springer International Publishing, pp 45–59.

Hao, K. (2019). The computing power needed to train AI is now rising seven times faster than ever before. [online] MIT Technology Review. Available at: <https://www.technologyreview.com/2019/11/11/132004/the-computing-power-needed-to-train-ai-is-now-rising-seven-times-faster-than-ever-before/>.

IDC: The premier global market intelligence company. (2022). IDC - IT EXECUTIVE - AI. [online] Available at: <https://www.idc.com/itexecutive/research/topics/ai>.

Keding, C. (2021). Understanding the interplay of artificial intelligence and strategic management: four decades of research in review. Management Review Quarterly, 71, p.91-134.

Lee, J. et al. (2019). Emerging Technology and Business Model Innovation: The case of artificial intelligence. Journal of Open Innovation: Technology, Market, and Complexity, 5(3), p.44.

McKinsey. (2019). Driving impact at scale from automation and AI. [ebook] McKinsey. Available at: <https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/McKinsey%20Digital/Our%20Insights/Driving%20impact%20at%20scale%20from%20automation%20and%20AI/Driving-impact-at-scale-from-automation-and-AI.ashx>.

McKinsey Global Survey. (2021). The state of AI in 2021. [ebook] McKinsey. Available at: <https://www.mckinsey.com/business-functions/quantumblack/our-insights/global-survey-the-state-of-ai-in-2021>.

Merritt, R. (2020). What is MLOps? NVIDIA Blog. Available at: <https://blogs.nvidia.com/blog/2020/09/03/what-is-mlops/>.

Microsoft Azure. (2020). What is DevOps? DevOps explained: Microsoft Azure. DevOps Explained | Microsoft Azure. Available at: <https://azure.microsoft.com/en-us/resources/cloud-computing-dictionary/what-is-devops/#practices>.

Mikalef, P. & Gupta, M. (2021). Artificial Intelligence Capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management, 58(3), p.103434.

Nexus FrontierTech. (2020). Human in the loop: Efficient AI system connecting humans and machines. Nexus FrontierTech. Available at: <https://nexusfrontier.tech/human-in-the-loop-efficient-ai-system-connecting-humans-and-machines/>.

Ng, A. (2021). Bridging AI's Proof-of-Concept to Production Gap. [online] Towards Data Science. Available at: <Bridging AI's Proof-of-Concept to Production Gap | by Kenneth Leung | Towards Data Science>.

Pumplun, L., Tauchert, C., & Heidt, M. (2019b). A new organizational chassis for artificial intelligence-exploring organizational readiness factors. In: Proceedings of the 27th European Conference on Information Systems (ECIS), Stockholm & Uppsala, Sweden.

PwC. (2017). Sizing the prize. [ebook] PwC. Available at: <https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf>.

PWC. (2022). AI Business Survey. PwC. Available at: <https://www.pwc.com/us/en/tech-effect/ai-analytics/ai-business-survey.html>.

Rahman, W. (2020). Scaling AI: 5 Reasons Why It's Difficult. [online] Towards Data Science. Available at: <https://towardsdatascience.com/scaling-ai-5-reasons-why-its-difficult-6ea77b9f7d48> [Accessed 23 August 2022].

Reilly, A., Depa, J. and Douglass, G. (2019). Scaling AI: From Experimental to Exponential. [online] Accenture.com. Available at: <https://www.accenture.com/us-en/insights/artificial-intelligence/ai-investments?c=acn_glb_artificialintelmediarelations_11069538&n=mrl_1119>.

Sam, R., Kiron, D., Gerbert, P. and Reeves, M. (2017). Reshaping Business with Artificial Intelligence: Closing the Gap Between Ambition and Action. MIT Sloan Management Review, 59(1).

Stamford, C. (2018). Gartner Says Nearly Half of CIOs Are Planning to Deploy Artificial Intelligence. [online] Gartner. Available at: <https://www.gartner.com/en/newsroom/press-releases/2018-02-13-gartner-says-nearly-half-of-cios-are-planning-to-deploy-artificial-intelligence>.

Stamford, C. (2019). Gartner Survey Shows 37 Percent of Organizations Have Implemented AI in Some Form. [Press Release] Available at: <Gartner Survey Shows 37 Percent of Organizations Have Implemented AI in Some Form>.

Tessian. (2022). The Psychology of Human Error 2020. Tessian. Available at: <https://www.tessian.com/research/the-psychology-of-human-error/>.

The Economist. (2017). The world's most valuable resource is no longer oil, but data. [online] Available at: <https://www.economist.com/leaders/2017/05/06/the-worlds-most-valuable-resource-is-no-longer-oil-but-data> [Accessed 23 August 2022].

The Economist. (2018). Non-tech businesses are beginning to use artificial intelligence at scale. [online] Available at: <https://www.economist.com/special-report/2018/03/28/non-tech-businesses-are-beginning-to-use-artificial-intelligence-at-scale>.

The Economist. (2022). Artificial Intelligence in the Real World: The Business Case Takes Shape. [ebook] The Economist. Available at: <https://impact.economist.com/perspectives/sites/default/files/Artificial_intelligence_in_the_real_world_0.pdf>.

Tse, T. and Karimov, S. (2022). Decision-making risks slow down the use of artificial intelligence in business. [online] LSE Business Review. Available at: <https://blogs.lse.ac.uk/businessreview/2022/05/18/decision-making-risks-slow-down-the-use-of-artificial-intelligence-in-business-1/>.

Ready to kickstart your Intelligent Automation Journey?

Book a free consultation with a data assessment and demo to accelerate your decision-making processes.

Schedule a Meeting

United Kingdom
Corporate & Sales

Japan
R&D & Sales

info@nexusfrontier.tech

Singapore
Tech, Sales & Marketing

Middle East
Corporate & Sales

www.nexusfrontier.tech

Vietnam
Execution & Delivery

About Nexus FrontierTech

Nexus FrontierTech accelerates decision-making processes by enabling modular automation solutions on our proprietary AI engine. We bring visibility, traceability and usability to enterprise data in real-time, empowering the financial services industry to efficiently develop structured processes for compliance, risk management, and innovation purposes.