# AI Strategy

## Video 1: Module Overview

Let me give you a sense of what I'm going to be covering in this module. I'm going to be talking about this idea of augmented intelligence. How maybe a tool like AI can augment the intelligence of organisations?

I'm also going to talk about how firms can jump on the AI bandwagon. So, I'm going to talk about a few of the implementation strategies. There are maybe different stages of firm's evolution in so far as adopting AI. I'm going to be talking about these different stages and how firm and for how firms can actually adopt AI itself. I'm also going to be talking a little bit about organising AI within your firm. In specific, I'm going to be talking about organisational structure that would facilitate the implementation of AI. Like with most things, implementation of new technologies involves trade-offs, I'm going to be talking about few trade-offs while implementing AI within your respective firm. And finally to capital off, I'm going to be talking about some of the pitfalls of AI itself. It's not a one way speed. Not everything is positive. Everything has a set of pros and cons.

And for a change, I'm going to be talking about the cons of AI as well at something that, as Managers, you might want to watch out.

## Video 2: AI Algorithms

Before I start off with this module, let me give you a recap of the previous modules. We spoke about different kinds of algorithm that are under AI. So, AI comprises broadly of machine learning and deep learning. And under machine learning, we spoke about supervised learning, unsupervised learning and reinforcement learning. And under deep learning, we spoke about this idea of convolutional neural networks and recurrent neural networks, right. So, the idea is that to take you through some of the technical details and so far as you can discern its utility and start thinking about solutions for business problems within your respective organisations.

So, the two major sets of algorithms that we spoke about is machine learning and deep learning. Machine learning is actually used for deduction of patterns for large amounts of data. So, the idea is to mine large amounts of proper data to come up with predictions for the future. And these set of algorithms also adapts to new data and mainly uses structured data, such a sales, production data, HR and so on; something that by now you should be familiar with. On the contrary, deep learning comprises of algorithms that essentially mimic the human brain. We spoke about this idea of how images are discerned, like how images are discerned by human beings using the visual cortex in the brain. And deep learning is typically used for unstructured data, such as speech, videos, images, and so on and so forth. It primarily uses neural nets. We talked about two forms of neural nets, convolutions neural nets and recurrent neural networks; and when they can be used as well. And these networks, neural networks can take vast amounts of input data and structure them as multiple layers in order to figure out patterns in these data.

And believe it or not, just like the human brain try, tends to figure out patterns from things that are abstract, such as images, voice and so on, these convolutions neural networks can also discern patterns from images, voice and so on and so forth. In that sense, we are getting very close to intelligence; human intelligence as well.

Although we are not there yet, these technologies or these algorithms have the potential to get us very close to human intelligence. Can you take this following poll? Could you now give me your favourite machine learning algorithm? Remember, I'm not talking about deep learning here, but I am talking to you about your favourite machine learning algorithm. Can you tell me why or can you think about why this might be your favourite?

**Video 3: The Missing Middle: Augmented Intelligence**

Let me now take you through this idea of augmented intelligence. But before I take you through this idea of augmented intelligence, let me tell you what the point of talking about augmented intelligence is all about. Recall that we started off with this debate, saying whether AI is going to replace human beings, right? We made couple of points in the same module as well. The idea that AI has the potential of being a general purpose technology, simply because it's applicable across a range of sectors and across a range of different tasks within this organisation. So, where does that leave us in terms of this debate?

So what I'm going to impress upon you is that, unlike other automation technologies, or even other kinds of technological breakthroughs like we might have seen before, AI has the capability of augmenting human beings. It's not going to replace human beings, but it's is going to augment human beings. It's going to augment the intelligence of human beings. Remember that we also saw a few examples of how AI might actually complement human beings, such as the case of doctors, such as the case of administrators or such as the case of even people who are trying to figure out fraudulent transactions in the case of a global buying. So, I am going to sort of zoom in to that idea of augmented intelligence, the idea of how AI might actually complement human beings rather than replacing them itself. So, I'm going to make the case that AI increases the size of the Pie. What do we mean by increasing the size of the Pie? The value addition of AI is essentially going to come about because of this idea that AI might essentially complement human beings, not simply replace them. If AI is simply going to replace human beings, the value addition is probably meagre. But what I am actually going to talk about right now, is this idea of augmented intelligence; the idea that AI essentially complements human beings within an organisation, which is where the big value addition of AI essentially comes into play. That, and where are some of these ideas going to come from, right, some of these ideas of augmented intelligence going to come from?

One, as we have spoken in the case of the examples that we saw earlier, by redeploying human beings to more sophisticated tasks. It's essentially going to redeploy human beings, like in the case of these fraudulent transactions; sifting in the case of global bank. AI can actually replace human beings for mundane tasks, but that's not going to make the human beings go away. But human beings are essentially going to be deployed to more value-added tasks. And as an organisation, right? You, the human beings can essentially had more value simply because of the fact that AI has been deployed for sifting through some of these manual and mundane tasks. Similarly, what's even more? The big source of value addition actually comes from the second point, which is as follows. AI can actually aid human beings to make better decisions. Like in the case of doctors who have to diagnose cancer. Like in the case of education; people and education, who might otherwise have to do this grading and so on and so forth. The AI has the capability of increasing the intelligence of human beings. And that's where the big value addition is actually going to come in, because of AI. And this is unprecedented. No other technology or no other technological breakthrough in the past, has probably had the potential of augmenting the intelligence of human beings within organisations. Let me actually talk through this in more detail. Humans can complement machines. This is one contribution of humans to machines itself. And how? If you are wondering how, humans essentially train AI on the right values and how they should actually perform. So it's essentially human beings which are, as guiding the algorithms about what to find, what kinds of predictions to do and so on and so forth. So, human beings play a part or contribute to AI on one hand by providing it with the right set of values, judgement, right? What kinds of things, or what kinds of output should be predicted? What kinds of inputs should be fed into the algorithm, right? So, that's what human beings are essentially doing.

Human beings are also interpreting some of the outputs that emanates from these AI algorithms itself. Interpreting the black box results of ML and making it transparent and actionable and converting them to business insights. So that's something that human beings are doing, right? Human beings are providing inputs. Human beings are using the outputs to take these predictions and transform them to business insights, right? The third way that humans essentially compliment machines is by ensuring the quality of data. You might have heard this concept of garbage in, garbage out. If you feed bad data, you are going to get bad predictions and these need not become actionable business insights. Human beings, by ensuring data quality, are going to ensure that AI is used optimally within organisations. It's used in a way by which it can actually provide intelligence to human beings within organisations. On the other hand, AI also gives humans superpowers. How do they do that? Well, for one, this idea of redeployment. It enables human beings to be redeployed to these more value-added tasks, so that they are actually adding more value to the organisation. Not adding less value, but adding more value to the organisation. While AI takes over the mundane, non-complicated or non-complex tasks. So, it enables managers to focus on greater value-added tasks. The second way by which AI complements human beings, is that it simply provides them with intelligence, right? It provides them with the capability of making better decisions, which is why it transforms the standard human to superhumans, by providing them with superpowers. And finally, this whole idea of mutual learning between human beings and machines, enhances the value both of the machine or the algorithms as well as that of the human being. So, here is how AI gives superpowers to human beings or employees within an organisation. And humans and machines sort of work together to provide mutual learning, which increases mutual productivity as well. And this is where the big value additions actually come from. Two ways to augmented intelligence; there are at least two ways to apply AI within an organisation, right? So, the bottom line of what we have spoken in the last couple of minutes is this idea, right?

There are essentially two ways to, to adopt AI within an organisation. What could they be? Well, it's the standard automised automation that you could try. Automation of mundane tasks, typically something that employees would do. You could automate them with an organisation. But then pause and think for a minute. That's exactly what every kind of technology, including, for instance, the RPA typically does. You could use any kind of technology to automate mundane tasks within an organisation. This is in the nature of other technological breakthroughs that have significantly aided, employees or firms in the past. Employees; but the big difference over here is that you could then take these employees and redeploy to other, maybe more value-added tasks. But wait a minute. This is typically what any automation technology would do. But the big value addition is in this idea of collaboration, right? By providing more intelligence to human beings and human beings working with machines to make the machines more intelligent. This is where the big value addition comes into the picture, and this is where AI adds significant value to the organisations not because just because of the former, but also because of this idea of collaboration. And this is what adds significant value to organisations due to the adoption of AI. And this is new, right? This is very, very different from any other technological breakthroughs that have aided firms in the past. And the way is to, for managers, the take away is to provide an environment or to set up machines and humans to collaborate with each other, so that their respective intelligences are mutually enhanced, right? So, the key to success if you believe in this idea of augmented intelligence, the idea that value; significant value addition comes from mutual learning, then the prescription over here is to set up machines and humans in such a way that they can actually collaborate and learn from each other. Recall the BMW example of brake linings that we saw in the past. The idea, maybe the success of BMW is because of the fact that some of their managers set up machines and human beings such that they can collaborate and also mutually learn from each other. To recap, the big value addition essentially comes from collaboration. And, why? If you pause and think why that might be the case, it's because both human beings and AI are mutually learning systems. It is really the first time in the history of humankind, that we have come up with a technological breakthrough that can actually learn much like what human beings actually do. So, now what we have, if an organisation adopts AI, is we have two mutually learning systems. This is really the first time that we have these two mutually learning systems and because of having another mutually learning system other than just human beings, organisations can actually enable the collaboration between humans and machines and significantly add value to their respective organisations.

And the key to success is about harnessing the capabilities of both human beings and machines, right? To complement human beings with machines and to complement machines with human beings. That is critical for the successful, value addition to organisations and therefore, the long-term competitive advantage of organisations as well.

### Video 4: Developing an AI Strategy

Now that I've told you how AI adds value to organisations, the question that you might actually have in your mind is how do I go about developing or adopting AI in your respective organisations?

So, let me talk a little bit about developing an AI strategy itself. Strategy for adoption of AI for your respective organisations. To give you a brief overview of where I'm going with it, there are different stages of adoption of AI within organisations. The first one is about awareness, creating initial interest and communicating that interest across the organisation. And then, you get to the active stage which is all about experimenting with AI before you go on for mass or large scale adoption. And then you get to the operational stage, which is all about limited deployment of AI within the organisation. So, once you have experimented, you understand the different features of AI and how it can aid your business. Then you try it out in a limited way which is what the operational phase is all about. This is about limited deployment of AI in the organisation. Then eventually, once you're convinced that AI is going to be very beneficial and you can actually create a set of applications using AI, the next stage is about being systematic. AI becomes a part of your core business models and you're thinking about how AI can actually add value, well and beyond the operational use of AI to automate tasks within your respective organisation.

And finally, you're talking about the transformational stage, where an AI itself becomes a core part of your business strategy. So, you're thinking about AI when you're thinking about different strategic aspects of your business, And that's when AI starts to influence your long-term competitive advantage.

### Video 5: Defining the Roadmap - Part 1

So, let me talk about the awareness stage. So, the goal over here as a manager is simply to create awareness of AI in your organisation. You could use communication channels, both formal and informal communication channels, and encourage people to think very broadly about how to adopt AI, for which kinds of business problems, within your organisation. From those, you might pick a few for a pilot, right. People come up with ideas.

You could set up a committee that actually looks and picks a few ideas for a pilot. You might also want to dedicate a small budget for the pilot as well. So, the goal of this step is essentially to create awareness of AI and how it can benefit your business and then to have people propose a few ideas from which you can actually pick a few and start off a pilot. But if you want to really start off a pilot, you might also want to dedicate a small budget for the pilot as well. In the active stage, you are actually creating projects which have POCs, or proof of concepts, for a particular idea of using AI within your organisation. You are also developing cross-functional teams for the pilot; just for the sake of pilot, you are creating temporary teams which might be cross-functional in nature. The keyword over here is actually 'cross-functional' because you not only want technical people, right. I don't want you to think about AI as a... simply as a technical tool. You want to create a cross-functional team that involves both business people as well as technical people who can actually work together for the purposes of this pilot. So, you are thinking about creating an organisation structure to monitor, learn as well as refine, right. So, you're learning but once you learn, you also want to refine the process of adopting AI within your organisation. You are also thinking about creating organisation-wide meetings about AI for knowledge sharing and sharing of these best practices that are emanating from the implementation of the pilot project. And you are also creating a budget for experimentation, right. So, once you've tried a few pilots, you've figured out what the best practices are, the next stage is to try more of such pilots or to experiment more broadly, for which you are creating a budget for experimentation. The most common mistake with the adoption of AI is that most managers come in with this IT kind of lens and approach AI using the same lens as well, the 'IT hangover'. So, they... which would eventually mean that the focus would rather be on automation rather than augmentation of human decision-making and interactions. So, we spoke about the importance of augmentation relative to simply automation. Augmentation is what adds more value to the organisation. So, you are leaving money on the table if you are actually focusing only on automation rather than augmentation. So, the mere focus on augmentation would result in the missing the hidden opportunities that result in greater value that emanates from augmented intelligence that AI essentially facilitates. And the recommendation over here is that you might want to look for cases, or business cases or use cases, with the following set of attributes. Attributes... these attributes are: Projects that can add mutual value addition between human beings and machines for which you already have large data that is available. And once you have both of these, you might then want to consider how AI might actually augment those efforts and maybe even create more value to your firm. In this stage of experimentation, right, in the stage of pilot, which is eventually going to lead to large-scale experimentation, you might also want to think about how do you develop a business case for AI. You might want to consider the following issues: Why are you doing this project in the first place? Is it because of cost saving, revenue benefits that would accrue to the organisation? Who's the target audience? For whom are you trying to deliver this solution? Collaborators who will work with the technology and be augmented is another target audience that you might actually want to think about.

So, the target audience need not be the end consumers; it's also about the managers whose intelligence will also be augmented. So, you want to think about collaborators who will work with the technology and also be augmented. And you may... at this stage, you might want have a broad sense of what solution and technological framework that you would employ, right. So, you are also asking these technical questions. Although AI is not completely a technical tool, you... technology is nonetheless important for the algorithms to deliver value to your organisation, and hence, you might also want to think about what solutions and technological frameworks you will employ. Technical questions as which kinds of algorithms, what kinds of data sources that you would use to deliver the intelligence to human beings or the... your target audience is something that you might want to consider as well. And you might also want to think about implementation issues. How will you deliver this project? Who needs to be involved? What kind of structures do you need to create? All of this would factor in developing a business case for AI.

**Video 6: Defining the Roadmap - Part 2**

Let me talk a little more about how do you go about adopting AI within your respective organisation? So, defining the roadmap, little more on defining the roadmap for adoption of AI. The next stage is the operational stage. You're moving a successful pilots to production. Right? So, you are also using the learnings and disseminate these learnings across the organisation. You are also actively developing and sharing best practises. And you're also going to identify experts within the organisation that are accessible to the entire organisation, right? So that you know the other projects that are going to be implemented, should they run into rough weather, they can actually contact these experts and figure out what needs to be done. You are also developing technology that is accessible to the entire organisation. So, you might want to think about a technological stack that can be used right across the organisation, across different functions, right? So, you're using some of these algorithms and writing an organisation's specific technological stack that can be reused across the organisation. At this point, as a manager, you are also thinking about developing a dedicated AI budget for other kinds of production projects, right?

You are also thinking about best practices for cross-functional teams for AI implementations. So, which kinds of people need to be a part of these teams? What kinds of organisational structure? So, I'm going to talk a little more about organisational structure when you're trying to make AI, when you're moving into the operational stage as well. And you might want to create clear directives or ownership who should own the AI algorithms as well. Organisation wide applications might need to be owned by the corporate office because it needs to be a shared resource. Applications that fulfill specific divisional goals need to be owned perhaps, by divisions. And functional specific applications need to be owned by those functional areas themselves. So, you are also trying to come up with a way of defining who should be owning these algorithms themselves, right? So that this facilitates the creation, the consistent creation of value across your organisation. You're also creating specific performance rubrics for AI across divisions and different functional units. Because measurement is really important for knowing whether AI is actually fulfilling the goals.

You might want to keep a tab on the kind of value addition that AI is creating across your organisation. Let me talk a little bit about organisational structure for AI. Structure is important because structure not only influences your AI strategy, but your AI strategy is also influenced by structure. The success of your AI effort also depends on the structure that you're putting together for some of these projects, right? So, structure enables strategy. Structure also influences strategy. So, the relationship goes in both directions as well, which is the reason why it's important at this operational stage to get the organisational structure right for the implementation of AI. We have spoken about this idea of assembling cross-functional teams. But how should these cross-functional teams actually work? How should work be divided across these different players? How should they be reaggregated or coordinated across these different people within the AI, within these teams themselves. So, before I get to that, there are a few elements of organisational structure that needs to be understood and this is a standard concept and strategy implementation itself. The couple of considerations that you might need to bear in mind or three considerations more precisely that you might want to bear in mind is, where is the your decision making power actually concentrated, right? Who should be making decisions, given the nature of these AI projects themselves? What should be the formal division of the organisation into different functional teams. So, how does the team itself divide itself into sub-teams and what is actually that all of every sub-team, right? So, yes, you could have one sort of team but this team needs to have sub-teams. How should you divide them into sub-teams and what should be the role of different sub-teams? And finally, the minute you have divided them into teams, its also important enough to aggregate them, right? So, it's important to aggregate their actions because what we're thinking about over here is, for creating value for the entire organisation, not just for this sub-team. So, that would employ that the idea of how do you coordinate between the sub-teams becomes equally important.

You might want to consider a few structures over here. So, what I'm calling as vertical differentiation? There are essentially, two different kinds of structures that might actually work for the implementation of AI across the organisation. The first one is that of a flat structure, which as the name itself connotes, is pretty flat. There are not too many levels. The second one is a tall structure which has multiple levels. There are several pros and cons that you might want to consider as managers while of these two different structures while implementing AI in your organisation. The obvious pros of flat organisational structure is better communication. There are fewer levels and hence, the communication is very fast, the decision making is very fast. There is also a greater motivation, right? Because everybody has maybe a larger span of control and this in some ways creates these big, you know, it acts as a big motivator, right? The con of having a flat structure is that it might not be scalable. There might be limited capacity and it might get very, very difficult to manage with large scale, right? So, the minute you scale up to different AI projects, this may not be a structure that necessarily actually work. As you would imagine, there are several pros and cons of a tall organisation structure as well. For one, the size and complexity can easily be managed. So, this is a far more scalable structure. As you scale out the number of AI projects within your firm, you know, this might actually scale very well as well. The second big advantage is that it facilitates greater specialisation. Simply because you have multiple levels, it also facilitates greater specialisation as well. There are cons of the tall organisation structure as well. There might be a lot of inefficiency in bureaucracy and it might impede communication as well. And this bureaucracy might translate into poor communication and coordination across different people within these structures themselves.

The minute you're thinking about a cross-functional team, you are also probably thinking about a matrix structure. So, relative to both the flat as well as the tall organisation structures, you're also thinking about a matrix organisational structure.

The advantage of matrix organisational structure is each given individual within a team or a maybe a manager within a team would essentially report into two different sets of people. One on the business side and one on the technology side as well. So, given that AI is a mix of both technology as well as business applications, you might want, you know, to set up this matrix kind of a structure, in which every individual who is a part of a cross-functional team, reports both into the business head as well as the technology head as well. But this is also not devoid of any cons as well. This whole idea of duel reporting means that there might be conflict. There may not be very clear accountability. People need not be necessarily aware of what they are actually responsible for. And this might also mean that people become more generalised rather than becoming specialised. And there are benefits to specialisation, hence, which may not emanate from this kind of a structure as well. But the minute you are thinking about cross-functional teams, maybe you are thinking about some sort of a matrix structure. And perhaps, the matrix structure will be better position for implementing AI within your respective organisation, provided you are able to overcome some of these issues that we spoke about, such as that of conflict, unclear accountability and limited specialisation as well. So, once you have systematically implemented AI across organisation, you then move to the transformational stage, right?

This is when you are thinking about moving AI into the boardrooms. Remember, the board is essentially overseeing a lot of these AI projects, including the experimentation stage. But in the transformation stage, we're talking about imbibing AI into the strategic planning of a firm itself, so that is what is going to create the long-term competitive advantage for your respective firm. And that is when you are going to realise, this value that AI is generating for respective organisations in full. So, the transformational stage like I spoke about, is to ensure that AI is incorporated into strategic planning. The idea is to develop and communicate with clarity about however AI can power competitive advantage within your respective organisations. So, when you're developing a business strategy, you are also thinking about how AI can aid in your competitive advantage as well. And since, central resources are owned by the corporate office, you are trying to ensure consistency with the corporate strategy as well. In fact, I would go one step higher than that. I would even say that you would always you could also look for opportunities to let AI determine your strategy and hence, the competitive advantage of firms. You're also thinking about rationalising ownership at this stage, right? Such that the public good that AI has actually created, right? You're thinking about who refining ownership of these different algorithms that you have all already implemented within your respective organisations. You are thinking about rationalising this ownership in the sense that you might want to centralise, like we spoke about the functions or AI algorithms that are of wide use for the organisation, useful across a whole range of divisions and maybe functional areas as well. On the other hand, the ones that has limited use, you're thinking about rationalising ownership by transferring to respective divisions or these respective functional areas.

**Video 7: Managerial Tradeoffs**

Let me talk about some of the managerial tradeoffs that are involved while implementing AI in your respective organisations. These managerial tradeoffs essentially emanate from the complexity of some of these algorithms and it's relative risk in terms of adopting it for the side of business problems that you might try and solve in your respective organisations. So, the first thing to remember is we have been through a bunch of algorithms. These bunch of algorithms can be classified right from linear regression, decision trees to K-nearest neighbours which is an algorithm that relates to unsupervised machine learning. Random forest which is another tree-based algorithm, support vector machines which is another supervised learning method to deep neural networks. So, deep neural networks can be used either in machine learning as well as deep learning as well. So, the point that I'm trying to convey over here is that these methods, you know vary in terms of their interpretability and accuracy as well.

So, the higher the accuracy that you might actually desire, you might need to make come down on the interpretability because the more accurate methods are some wh out of a black box, and it's very difficult for managers to derive business insights from whatever these methods actually spit out. On the contrary, if you were to choose an algorithm that was less accurate, like for example linear regression, which essentially tries to fit a straight line with the data. This might be less accurate but it comes with the big advantage of interpretability. It's relatively easy to derive business insights from linear regression model. So, managers might carefully think about these relative tradeoffs, if whether accuracy is relatively important, relative to interpretability as well. Methods that are easily interpretable may not be very accurate and vice versa. So, managers have to tradeoffs the risk of accuracy with the ability of these algorithms to provide business insights, which crucially depends on interpretability of these algorithms. So, managers should actually also think about the extent of data that is required. So, more accurate models might require greater amount of data simply to be able to make these accurate predictions. So, the data requirements also will have to be taken into account when managers make this tradeoff between accuracy and interpretability. But on the contrary, the lack of accuracy could also be risky. So, managers will have to carefully think about the business problem, the amount of risk that is involved in terms of getting these predictions incorrect relative to the amount of data that might actually be required and even the effort that might be required to make these accurate predictions as well. So, this is one of the tradeoffs for managers to take into account before they jump on the AI bandwagon for a given business problem. There is a different tradeoff that managers need to take into account as well which is the tradeoff between short-term risk, the risk of getting predictions wrong and the associated business risks that come about when these predictions are wrong relative to the difficulty of adoption.

This difficulty of adoption is mainly on account of being able to collect accurate data in large scale as well because a lot of these algorithms require data on large scale. For example supervised learning could be high-risk exercise, especially in the short-term as well as very difficult adopt. Why would it be difficult adopt? Simply because the supervised learning algorithms, since they're trying to predict an output, would require immense amount of data collection, immense amount of structured data collection and which might be a very difficult exercise for firms that are simply beginning the process of digitisation itself. On the other hand there could be high-level of short-term risk, assuming that these algorithms take a long time to figure out patterns in the data, especially if you have large amounts of data, figuring out patterns in this data might actually take you a very long time and hence, at least in the short-term, these risks might actually be very high. On the contrary, reinforcement learning could be something in which the short-term risks are very high because you are allowing the algorithm to play with the environment and through the process of reward system, you are letting the algorithm come to an optimal decision so that might at least in the short term, until the algorithm figures out what the optimal decision is, since it's actually playing with the environment, the short-term risk could be very high.

On the contrary, the data requirements could be very low, which is the reason why it might be easy enough to adopt. We are simply allowing the algorithm to play with the environment which simply increases the risk but not the difficulty of adoption. Deep learning on the contrary, could be something that involves a low short-term risk. But maybe it is high in high difficulty of adoption. Why? Because deep learning involves lots of digitisation of data. If you're thinking of figuring out patterns from photographs, you would require large amounts of data to figure out patterns from these photographs. So, digitisation of these unconventional pieces of data or unstructured data is a necessary precursor for deep learning which makes it perhaps very difficult to adopt. But on the contrary, to the extent that you are simply trying to figure out patterns and maybe not make predictions, so maybe the risk is a little bit low. Once again, the caveat over here is to is dependent on the kind of applications that you are planning to use deep learning for. If for example, you're using deep learning for automated or autonomous vehicles, you know the risk is relatively high. But let's say you are simply using it for discerning images and figuring out patterns from images and figuring out the effectiveness of your brand. The relative amount of risk in the short-term could actually be very low. So, the the categorisation in terms of the these axes in terms of risk and difficulty of adoption, is mandated on the nature of applications that you're going to be using these for. And I'm assuming that deep learning over here is not being used for an application that is as important as autonomous vehicle driving, for example. Finally, unsupervised learning which is just an exercise of trying to figure out groups in the data. So, there is no output, there's no prediction, it is simply to figure out groups in the data by be something in which the risk is very low. So, misclassifying customers in the short-run is not going to be a very big crack to your business.

You know, supposing you figure out the wrong segment of customers. Yes, you could always learn by you know, through a process of refining either these algorithms refining your learning as human beings. So, the relative amount of risk could be very low and at the same time the difficulty of adoption could also be relatively low simply because you are not looking for label data. You're simply looking for unlabel data which might be a little bit easier in terms of the risk of adoption or the difficulty of adoption itself. So, here is an example of how firms make these choices. Here is a survey from KDnuggets Poll which suggest that the easiest of these algorithms are essentially the ones that tend to be used at the maximum. And this is not a surprise because right now we're at a point wherein businesses are simply trying to adopt AI. Most of the businesses simply trying to adopt AI rather than to refine it which is why there is this tendency for businesses to sort of rely more on interpretability rather than accuracy. Regression clearly is something that is not very accurate, but it's easy enough to interpret, is clearly at the top of the file. And as you come down so, things like neural networks, convolutions neural networks or general neural networks itself seemed to be less popular, simply because neural networks tend to be a bit of a black box, which means that it's incredibly hard for managers to use these algorithms and derive business insights. Whereas the ones that are easy enough to derive business insights from are tend to be the ones that are incredibly popular as well. So, you can already see that this managers are exercising these choices and to maybe over a period of time, this picture is likely going to look different.

As managers become more and more conversant with these technologies, maybe the more accurate technologies might become also more popular, simply because managers make simply get used to using these technologies and derive business insights from.

**Video 8: Problems and Limitations with AI - Part 1**

So far, we've been talking about a lot of positives about AI, but like with most things, AI suffers from a few problems as well and managers need to take these into account before they decide on adopting AI. Although of the adoption of AI, given that it's a GPT might be inevitable, managers would need to figure out antidotes to some of the problems that I am going to discuss right now. The first problem is that of biases, right? Human beings carry a lot of biases.

Some of them are visible, some of them are invisible and it's quite plausible that these biases might creep into these algorithms as well. And if they do creep into the algorithms, it, these biases might be much harder to correct than with human beings, right? Why would that be the case? Simply because AI sort of scales up these data analysis and interpretation as well. And it might be very, very difficult to scale back, on some of these biases, especially the consequences of these biases. But AI in healthcare in general faces lots of biases, right, because the neural inputs of humans creeps into the data is essentially passed on to the algorithm and starts to be embedded in the algorithm, right? But, something that maybe the this side of analysis does not take into account is that in healthcare, for example, there are both implicit and explicit unconscious biases, right? For instance, biases actually exist in how patients of different ethnic groups are treated for pain, right? There is a lot of study which suggests that, you know, patients of colour are treated very differently for pain relative to patients of a different colour, right? So, this is documented and, you know, this is actually recognised now more so than before in the healthcare literature and the treatment for pain or any other kind of disease also varies by doctor, the doctor's gender and the cognitive load that the doctor is facing at a given point in time. If you think about these, estimates and if you put the estimates from the perspective of what I just said about these human biases, it's quite plausible that these, these biases which emanate from the data generating process which are essentially collected by human beings, also creep into the algorithm, right? So, the question is that how do you really paddock these algorithms such that they're actually free of these biases. So, it's important for you as managers to think about these implicit as well as this explicit hidden biases and think about how to mitigate them in terms of the data that you are feeding into these algorithms, AI algorithms.

The second thing is that once you've already deployed and you've starting to make predictions based on, biased data, it might be very difficult for you to scale back, right? Relative to letting human, human beings do these certain types of cognitive tasks. Right? Simply because human beings, for example, doctors can actually be trained for these unconscious biases. We spoke about these different biases in healthcare, right? So, the variation by race, by gender, by the cognitive load that the doctor is facing, you know, you can provide training for all of these things, right? And human beings can be trained and corrected even at a subsequent stage, and in order to mitigate these biases. Since AI works with the large scale data, and once you deploy AI, you know, it's not obvious whether how you reverse some of these biases as well, right? So, that's something that's very important for you to think about, especially it's important for you to ensure that the initial data or the training data that you feed in to the AI algorithms are essentially unbiased and don't suffer from explicit or implicit hidden biases. The second sort of drawbacks is something that we've already spoken about, right? It comes from the idea that some of the algorithm, some of the AI algorithms can actually be a blackbox. Why might this be a problem? The problem that emanates from the blackbox is that this blackbox, when the blackbox spits up certain kinds of results, it might be incredibly hard for managers to derive business insights from these blackboxy results.

To give you a categorical example, Neural nets maps variables to outcomes in very complex ways that might make it very, very difficult for a simple manager or a lay person like me to sort of figure out the relationships between certain kinds of input and output variables. This makes the links and the intermediaries between variables very fuzzy and even the creators of the algorithm can barely discern these relationships as well. Right? If it is so hard for the creators to discern these relationships, what chances do managers have in terms of understanding what the algorithm spits out and, in turn, deriving business insights. Remember, the goal of manages to derive business insights from AI. That's when their intelligence is essentially augmented. So, the bottom line is AI is susceptible to the same biases as human beings, but the point is that the computing power might scale it up considerably, right? And one thing for you to remember in the context of the blackbox nature is also the fact that once, you know, the algorithms themselves are fuzzy and blackboxy, it's very difficult to figure out whether the algorithm is actually biased or whether human biases have actually seeped into some of these algorithms as well. So, although AI is susceptible to the same set of biases as human beings, AI could actually consider, considerably scale it up. And these biases might emanate due to missing data, the blackbox nature of these algorithms and simply because you have large amounts of data.

You give, you may not be able to overcome these problems because they might suffer from some foundational issues of measurement construct validity, reliability and dependencies among the data. So, once you deploy it and the blackboxy nature of some of the AI algorithms could essentially mean that you probably may not even have a sense that, you know, your data generating process is actually biased.

**Video 9: Problems and Limitations with AI - Part 2**

The second big issue with AI is this is not a problem of AI for say. This is just the fact that some of the managers may not be used to thinking about the difference between something that is causal in nature and something that is simply correlated. So, you know, the fact that the ground is wet, when it rains does not mean that when the ground is wet it is always rain, right? So, one is about causalities, the second one is about causation, right?

So, there is a correlation between the ground being wet and rain, for example. But the, there is no causalities right, the causalities may not be as clear between when the ground is wet and the fact, that it might have actually rain. So, you know, manages really need to think hard about what is correlated versus what causes what, right? Another example, is that it's often found that people, that there is a high level of correlation between people buying milk and people buying diapers. And this is just correlation. There is no causal explanation for it. There is no theoretical explanation of why both of these actually might be correlated, right? So, it's important for manages to actually think about, whether they are actually seeking correlations or whether they are seeking causality.

Causality is something when you are thinking about a variable X, creating or causing Y itself. That is very different from saying that X and Y are correlated. The common news of AI algorithms, right, assuming managers are trying to derive business insights from them is to predict somewhat, some kind of a behaviour, right? For example, anticipation of the next purchase of your customer or likelihood of employee attrition. Here, managers might be, must be very careful while taking actions based on these predictions, right? Because there is this prediction that the really, simply because X and Y are related, you know, that X creates Y, right, or X causes Y. So, managers might be very, must be very, careful in terms of acting on some of these predictions, and they must be careful enough to think about whether these are correlations or causations themselves, right? When X causes Y, you could figure out a way to moderate the levels of X, so that you can then influence the levels of Y. But if these are merely coordinated simply taking an action or next we're not mean that you're moderating the levels of Y. So, managers might be very, must be very careful while taking actions based on these predictions.

Often, root causes are important, right, because managers are trying to figure out root causes for many of the business problems that they encounter. And predictions, which are simply based on correlations, may not necessarily be symbolic of the root cause or symptomatic of the root cost like, I just spoke about. For example, if you're trying to predict the segment that you should focus on to offer insurance policies, and you observed that there are two segments. Segment one uses health services more from the cumulative amount of hospital bills, whereas segment two uses healthcare services, less from evidence of the cumulative of hospital bills. You might actually decide, right? If you believe that these are causal in nature, the fact that segment one is spending a lot on hospitals and maybe they're need to go to hospitals is very high. If that's what your conclusion is, this is a causal conclusion, right? If this is what your conclusion is, you might decide to focus all your marketing efforts on segment one, assuming that this is the segment whose healthcare needs a very high. But if Segment two, for example, the fact that segment two does not go to hospitals as much a segment one, is simply driven by their low affordability. And hence, they are not visiting the hospital as much. Maybe a real business opportunity is actually on segment two and really not segment one. And that's what you should be focusing. That's the segment that you should be focusing your marketing efforts on, right? So, there are several examples like that, right? So, in this case, segment one, the correlation between cumulative hospital bills is correlation that's not driven through causalities, right? The real cause here is of affordability, which is not even picked up by the algorithm. So, if the manager decides to focus on segment one simply based on these correlations, the manager made actually be doing the wrong thing. There are several examples on these lines that one can actually give. But before thinking about these other examples, you know, it's important to think about whether predictions were correlated or weather predictions are causal in nature. So, several problems exist that implies that simply, simple correlations may not be causal in nature. For example, even if events X and Y are correlated, X need not cost Y, right? So, there are several reasons for it. In the case, of the healthcare algorithm, higher rates of illness were correctly correlated with higher healthcare cost for segment one. But if you are thinking about segment two this, correlation was not at play, right? Because what was driving the lack of correlation between cumulative hospital bills. And segment two was this idea that they were not able to afford to go to the hospitals, right? So, this the same correlation patterns that applied for segment one, was not applying for segment two, right? So, what ended up happening is that what was driving the correlation for segment one versus segment two is a different variable. Let's call it z (zee) or Z, if you would like, which is income which must have been considered, the algorithm failed to consider it, right? So, there was omitted valuable that the algorithm failed to consider which essentially lag to these wrong conclusions.

If in fact, the manager was simply focusing on segment one and focusing all the marketing effects, efforts on segment one. The bottom line is actions required understanding of root causes, rather than just prediction. It's important for manages to understand whether robust correlations are just enough for managerial action. On the contrary, it's also plausible that hospital prices, which is a component of higher health care costs, determines the rate of illness, right? So, this is known as simultaneous bias, right? Because you know, rates of illness depends on whether it's diagnosed or not. If it's very hard or very expensive for somebody to get diagnostic capability, then the incident rates of diseases which depends on whether these diseases are discovered in the first place or not, might also depend on the diagnostic cost. So, it's quite possible that the causalities actually goes in the other direction, right? This is typically known as simultaneous bias and statistics, and simply correlations need not mean that one variable causes the other. The relationship could go in another direction. The data could also miss people, who don't have access to former healthcare system. This is what is actually going on in the hospital example, and this is typically known as selection bias for those who are statistically minded. Another example could be that of precision agriculture. Precision agriculture uses data from satellite imagery and senses to help farmers to predict crop yields, right? So, there are several variables, that are actually used to predict crop yields, and these could simply be correlations. And these variables need not be causing the crop yields themselves, and a lack of understanding makes it impossible for any policy maker to take action to increase crop yields as well.

**Video 10: Problems and Limitations with AI - Part 3**

The other problem is something that might be more widespread, right and something that most of you as managers might already be aware of. Not all the organisations might actually be ready to adopt AI, right? For example, predictions depend or accurate predictions depend on the quality of data which for starters, require systematic data collection and sanitisation. Richer consideration or richer data that could, in fact, yield more accurate predictions might also get into somewhat of a set of privacy issues, right?

So, for example, if you want to predict customer buying behaviour and you want more demographic data of the customer, some customers could come back to say that wait a minute, aren't you asking me for private data? So, you could run into privacy issues but this kind of richer data is what is going to give you accurate predictions from the perspective of a manager who is trying to derive business insights, right? So, this might be a very difficult problem, right? So, the quality ensuring that you have rich, high quality and sanitise data might be an issue for many organisations depending on the sector that your organisation actually belongs to. Organisations also have to be fundamentally data-driven, right? In several parts of the world, like the, the act of digitisation is badly starting, right? Organisations are badly, especially legacy organisations are very badly getting started in on the process of digital transformation, and it's important to remember the digital transformation efforts might have to precede AI itself, right? It's important to remember that AI is strategic, not a tactical tool, right? And hence, you know, this amount of our maturity in terms of digital transformation would be an incredibly important precursor for AI to be effective in your respective organisation. More on why or not all organisations might be ready. Even if organisations have successfully digitally transformed themselves, you know, not all digital insights or whatever algorithms spit out might be useful for managers because managers have a particular mindset, right? So, managers are trained to think about, think about business problems in a particular way.

Managers typically learn from experience, learning and drawing inferences from data is arguably new for managers, right? Because most of them are used to coming up with actions for a given business problem based on their respective experience, and if you're going to go on present data to them and ask them to draw business insights and then subsequently take business actions. This is something that is arguably new for them, and this would require a significant amount of mindset shift on, on the manager's front. Managers, and it's been proven, right? There is lot of work in psychology which suggest that managers tend to make decisions using heuristics which ignore much of the information swirling around them, right? So, what they tend to do is that they try to simplify, simplify the problem as much as they can, and then to draw it, draw parallels with something that they have done in the past, and hence use that as a basis for making decisions itself. That is very, very different from using machine learning or artificial intelligence generally to make decisions, right, because these algorithms tend to give you a lot more information than the small world represent, small world representation that a manager might actually seek. Managers actually focus on specific cues without engaging in effort-intensive task of identifying and weighing large information sets. They come up with the small world representation, when confronted with a new or an unfamiliar problem based on their prior experience. And that's what is what they use as a basis for coming up with decisions, especially when they are, when they are encountered with an unfamiliar business problem. And complex AI prediction is exactly the opposite of the small world representation, right? Complex AI predictions will require significant amount of cognition simply to interpret the data and derive business insights from. And this which requires a significant shift in the mindsets of managers and these toolkits that they use to come up with decisions. And finally, on the same point that not all organisations might be ready. If your organisation is using an algorithm such as reinforcement learning, the complex trade-offs that the algorithm itself makes, right, could often be incomprehensible, right? We spoke about the move, the magical Move 37, which was criticised by a bunch of critics. Nobody understood this move.

Simply, because nobody could really follow through, no human being could really follow through on what kinds of trade-offs, short-term vs long-term, that the algorithm was actually making, right? So, the AlphaGo Move 37 that we spoke about earlier, was essentially came about by sacrificing, you know, different things that are making these different kinds of trade-offs which was completely incomprehensive, incomprehensible for human beings. Or, for example, the Stockfish 8 game chess, right, which was also based on this idea of reinforcement learning, right? The optimal decision suggested that a bunch of pawns be sacrificed in order to make the right move, and everybody, right, all experts in the chess world, thought that that was bizarre to start with until they found the final outcome of the game. So, a lot of these trade-offs in the short-term could be incomprehensible for managers so much, so that they may actually stop using this set of algorithms simply because they feel that the short-term risk could be very, very high. And some of these moves that the machine makes might be incredibly complicated, right? The trade-offs that the machine makes could be incredibly complicated, especially the trade-off between short-term, which I'm calling it as exploitation, vs the long-term, which is, which is what I'm calling as exploration. So, if these trade-offs are incomprehensible, managers are less likely to use these algorithms and use them as a guide for decision making themselves. In fact, they are even less likely to try it out in the fear of these costly short-term risks. To recap the point of giving you or taking you through this tour of some of the downsides of AI is not to discourage you from adopting AI in your respective organisations, right? But it is simply to warn you of some of the pitfalls of AI, right?

Some of the pitfalls that you might want to consider and figure out antidotes for is this fact that AI can sometimes be a black box and this black box, the problem of AI being a black box, could manifest itself in different ways. For one, it, you may not even understand whether there are biases in the data, and these can be in, these biases can be inadvertently passed on, from human beings to the trading data. And if you're drawing inferences based on a similar test data, this might actually create problems that you hadn't anticipated. So, the question is, how do you make sure that the data that you feed into these algorithms are free of these kinds of biases? Data collection can be a very big hurdle. Data, Digital transformation is a necessary and an important precursor for AI journey.

Managers need to carefully think about the importance of correlation vs causation. Managers often need root causes to take actions, but often it may not be the case that the AI algorithm are essentially giving you causal results, but they are merely giving you correlations. But it's important enough for managers to think through whether correlations are enough for them to take managerial actions.

**Video 11: Final Thoughts**

So let me leave you with these following closing thoughts about how to succeed in this world of AI, right? The first one is about a strong executive leadership, right? So I don't want you to go away thinking that AI is essentially a technical concept. It can be owned let's say by the IT department, like most other technology, pieces of technology that might already be existing in your organisation. Strong, successful adopters have to have strong executive support and leadership to implement AI. Especially to get to these transformational phase in which AI is essentially shaping your business and competitive advantage. If you want to really get there, then it's not about thinking about AI as a merely technical decision.

It's a strategic decision that would involve strong executive leadership as well. And adapters need not really think about adopting it by using their in-house technological capability, right? The idea over here, if you want to really get started very fast, the idea would be to leverage partnerships. So for at least for starters, you could start off by buying technology or technological solutions from outside, rather than simply relying on their in-house capability, right? Even large companies, technologically sophisticated companies like Google, have acquired DeepMind because they did not want to develop reinforcement learning from scratch. And deep mind was already on its way forward to developing lots of applications with reinforcement learning and Google simply acquired them. And the idea for Google was to leverage those partnerships to develop create value for its customers. And I don't see why organisation should exclusively rely on its in-house capability to embrace AI. The adoption of AI is a strategic decisions, right?

So once again, you know the, as just like the involvement of executive leadership is crucial, organisations cannot just leave it to their technical teams for the adoption of AI, right? This is something that I've observed many organisations doing at the end of the day. It's, once again, it's important for managers to think about AI as strategic. And if it is strategic, you can't just leave it to the technical departments or the technical teams. And these decisions of adoption, as well as refining AI, needs to be led by both business as well as technology leader. The key to adopting AI is also this idea of experimentation. So it's important to play around with these technologies to figure out what, which sets of technologies might actually work for. The specific set of business problems that you want to address, or even the strategic issues that you want to address in the long-term. In the short-term, you might want to focus on proven solutions and then scale them up across the organisations. In the medium term you want to experiment, and in the long-term, you might want to not only make as a part of your strategic decision-making, but also work with partners to solve many different cases and increase the value of the pie. Summary conclusions is that AI is a tool for long-term competitive advantage of firms. We spoke about this idea that AI is essentially a general-purpose technology. And early evidence suggests that AI is an all pervasive tool that would likely aid human managers to make superior decisions across a broad array of sectors and functional areas.

The strategic opportunities of several algorithms nonetheless have to be understood, right? And the ethical and privacy concerns about gathering and maintaining and sanitising large amounts of data have to be concerned as well, have to be considered as well, right? Which is why these ethical and privacy concerns, I need to be carefully considered before the adoption of AI and the transformation of a starts with a strategy. So we spoke about the implementation strategy. It starts with a strategy and coherence across these different businesses, divisions and across functional areas in terms of the single-minded focus of adopting AI and making a strategic tool is incredibly important for our long-term competitive advantage of funds. And finally, AI also involves, transformation of mindsets, right? So AI, like we spoke about, essentially goes against the traditional managerial mindset, is that of representing unfamiliar problems as a small world problem and ignoring data or read what managers typically tend to think as irrelevant data and simplifying a problem before they make decisions. AI essentially goes against that mindset. And using AI to derive business insights and subsequently take actions for managers requires a significant mindset change. And that's in say, in itself is an act of, requires an act of leadership to transform mindsets within organisations.

**Video 12: Module Summary**

Here are the key points that we've covered in module four, right. We looked at the value of AI to organisations, uh, uh, and the fact that the value, the significant value that emanates from AI for organisation comes from this idea of augmenting and complementing human intelligence rather than replacing them or automating a bunch of tasks that would essentially replace human beings within the organisation.

However, for organisations to reap the benefits of AI, especially this idea of augmenting or complementing human intelligence, an implementation strategy would be critical for the successful implementation of AI and therefore for the long-term competitive advantage of firms. So, we spoke about the different stages of implementation, um, and what firms should do in each one of these stages, including the kind of organisation structure that, that might be optimal for implementing AI within your respective organisations. We also spoke about some of the trade-offs that these, that managers need to consider while implementing AI. These trade-offs are obviously embedded in some of the technical features of AI, but there are business trade. These trade-offs are essentially business and related to business decisions, and these trade-offs would have to be considered by managers while implementing AI itself.

And finally, we spoke about some of the pitfalls of AI and the idea of pointing you to some of the pitfalls of AI is not to discourage you from adopting AI, but rather to get you to think about strategies that would mitigate some of this pitfalls of AI.