Thrive in AI disruption

Beginning with AI

3 Key Insights for Non-Technical Professionals

by Daniel Faggella

Research | Strategy | Competitive Intelligence

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2. Short-Term and Long-Term AI Investment
3. AI Adoption Motives
4. Timing and Purchasing of AI
5. The Three Phases of AI Adoption

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Introduction

In this era of AI disruption, professionals from every business function will be necessary for AI initiatives; those that can understand and leverage the business strategy of AI will be rewarded, just as easily as the technical professionals coding artificial intelligence programs.

AI adoption not only involves overcoming common pitfalls for AI adoption, it also involves taking on the right mindsets and the right workflows to better ensure success.

For that reason, this introductory guide to AI adoption is broken into three parts - tackling the challenges and opportunities of three key insights non technical professionals can utilize in their careers.

This introductory guide draws on three primary sources:

- First, our article series titled "The Pitfalls of AI Adoption"
- Second, our in-depth executive report, titled "Getting Started with AI: Proven Best Practices for AI Adoption"
- Third, best practices from some of our guests on our *AI in Industry* podcast

I've included a number of links to other Emerj articles when necessary, include industry-specific use-cases or additional context on terms or concepts.

Enjoy.

Daniel Faggella, CEO, Emerj Artificial Intelligence Research

Insight 1 - Adopting AI for the Right Reasons

What's harder than training an algorithm to detect images or automate a process? Collecting and cleaning the data in the first place.

And what's even harder than that? Integrating new AI systems into old technology, old processes, and old skill sets that exist in most enterprises and midsize businesses today.

This sort of cultural shift is arguably more challenging than the technical problems of AI. Computer vision and different kinds of NLP are rather proven use cases. They provide great value when you have the right data and the right setup, but baking that into an existing business is where the challenges arise.

This is what the vendor landscape of AI companies are trying to solve. They're all trying to become more accessible to the businesses of today.

Due to this accessibility issue, enterprises often jump the gun and make poor decisions; there are factors that they simply don't consider or factors that they often over emphasize. We interviewed vendors, consultants,and the buyers in big enterprises, to identify the top pitfalls of AI adoption.

These are things that the C-suite just misses or is overlooking:

- The Insidious Force of AI Novelty
- Underestimating Integration Needs
- Underestimating an AI Application's Time to Value

This guide will address each of these three factors, the first of which is what I call the insidious force of AI novelty. In this section, I'll talk about the worst case scenario of falling for AI novelty, as well as,, how to overcome it. One of these guides is called How to Apply Machine Learning to Business Problems, and I think it's one of our best. We also did an interview with Madhu Sekhar at Amazon about the best places to apply AI first in business and getting started with AI at one's company.

The Insidious Force of AI Novelty

The worst manifestation of the insidious force of AI Novelty is in looking for AI for its own sake.

Although not every executive needs to drag themselves and their team away from work to attend an AI event, as we outline in our executive guide on the topic, on the aggregate, continued interest in how AI is making a difference in one's sector is going to allow one to make much better decisions when they're ready to implement AI at their company.

One scenario I see often is business leaders looking for a place in their business to use AI when AI might not be the right answer to their business problem nor the key to driving value.

Looking for AI for its own sake involves starting with the question "Where can we use AI?" instead of asking about the best technology to solve a problem or increase revenue. Luckily, this doesn't happen as often as it used to because business leaders are becoming more informed.

More often than not, executives start to look for AI for its own sake after coming back from an event or a meeting where they found out their competitors are using AI. Sometimes it comes after reading a competitor's press release. The C-suite then feels they need to jump on so-called AI "toy applications" for their own sake to look competitive.

We've written about AI toy applications extensively in the past. In a nutshell, we consider an AI application a toy application when the company that's implementing it is doing so just so they can say they're doing AI. An executive at the company will see their competitor's press release about a new predictive analytics system for fraud detection, and they'll divert resources to procuring one from a vendor, too.

When they do this, they often fail to account for the extensive integration process that comes along with adopting AI in the enterprise and the time to value, which we'll discuss in a later in this guide.

They ask, "Where can we use AI?" instead of asking the better question, "What's the right technology to adopt into our business that could drive the most value?"

AI vendors will often play up the fact that their software leverages AI (even when in many cases it doesn't) because they know business leaders believe they should be using AI at their companies. That said, there are ways for business leaders to level up their skills when it comes to vetting AI companies and avoiding the lure of AI novelty; we discuss this in the next section.

Determining Whether AI is the Right Tool for the Job

Businesses should probably not even look at vendor companies if they don't have the capacity to leverage AI or a good enough understanding of where it could be used at their business. This requires a basic understanding of knowing what kinds of problems AI can solve.

For example, a hospital may want to find an AI software for diagnosing cancer in its patients. Machine vision software may be able to help, allowing radiologists to upload patient medical scans into the software and having it point out where in the image a tumor may exist.

The problem is that without the proper research, a hospital might believe that the machine vision software is flawlessly going to point out a tumor within a patient scan every time. That isn't the case. The accuracy of machine vision software can vary depending on how many patient scans it was trained on.

Right now, most machine vision software used for assisting oncologists in diagnosing cancer are trained to detect only one or two specific types of cancer. If the hospital wanted a software that could diagnose several different kinds of cancer, they'd likely need to build a software in-house, and they'd then have to ask themselves if they have enough of a history of patient medical scans to train the software on. They might even need to get patient consent to do so.

In this example, the hospital needs to ask themselves both where AI can be used in their business (answer: medical diagnostics), what the scope of what AI can do to solve that business problem is (answer: detecting only tumors in specific parts of the body in specific kinds of medical scans), and if it's even practical to implement AI to solve the business problem at all.

Insight 2 - The Realities and Challenges of AI Integration

This second section covers underestimating the integration needs of artificial intelligence and machine learning which is what many of our PhD podcast guests consider to be the biggest hurdle to AI adoption in the enterprise. Bringing AI into an existing business is a challenging task, and it requires a very specific set of concerns.

Integration Challenges

We'll begin our conversation here by talking about what we might refer to as how a run-of-the-mill IT integration works. There's no better example of this than something that recently came up at an event where I was presenting. At the time of writing this guide, I am just getting back from speaking at United Nations headquarters.

The UN is very interested in the security implications of artificial intelligence, and they actually had us create a deep fake video of one of the United Nations directors.

After the demo, I had a number of conversations with diplomats and law enforcement leadership. I had two conversations in particular with people who essentially asked how AI could be plugged into a video.

It's a reasonably complicated process. It's not a snap of the fingers. Unlike traditional IT solutions, AI systems have three distinct and unique challenges.

We'll break down the two main challenges of AI integration in the sections below:

Challenge 1: Data Infrastructure Needs

The first concern is data infrastructure, or how to make sure that the software that we are working with has the data that it needs on an ongoing (and often real-time basis) in order to help the business. Also, a company will need to ask if the data they do have is uniform and in a format that they could feed to a machine learning algorithm. In addition to all of this, the company will need to know if that data is truly accessible, compliance laws may block the usage or handling of certain data- preventing progress. In that same vein, data needs to be extractable from the silo it is contained in to prevent an error from tainting the entire set of data. As an example, imagine a sensor collection data for an AI model being accidentally blocked by a misplaced box, that sensor data may need to be accessible in order to remove the "box" data that has no true bearing on model.

Companies adopting AI need to make sure that the data is harmonized, that the fields of data are very similar across systems so that they can match the data within their system and model. This data must be input into the machine learning model; machine learning systems are constantly being trained.

How can companies consistently ensure that the data from all these different parts of the organization are able to come together in a way where they can train a machine learning system on it?

Challenge 2: Feature Engineering

This brings us to the second big challenge here that goes along with data infrastructure, which companies have to do before they even set up streams of data, and that is feature engineering.

When a company want to train a machine learning system to do something, leadership needs to determine what data would help it do that. Sticking with the fraud detection example above, let us look at the behavior of a logged-in user. What are they doing? What are they clicking on? What are their mouse movements?

Companies also need to know their transfers, their balances, the payments that they make from those accounts to their credit cards or to other vendors, etc. Companies need to track that kind of data and they need to determine what historical instances of fraud are.

These are just a few types of data that one might use to train a fraud detection system, but feature engineering involves a deep strategic process for determining what those types of data are in the first place.

That conversation of feature engineering almost always is going to involve two different parties: a party with data knowledge and a party with business knowledge.

It's going to involve people who understand data science, who know how to train algorithms, who understand the formats of data, the types of data, and the reasonable capabilities of machine learning. They would know what's realistic, what's unrealistic, what kind of data might a company be able to use to feed a system versus which ones a company might not. Companies building AI need people that understand the science.

Those companies also need people who understand the business. For a fraud detection system, subject matter experts in fraud and banking. These people don't have to be AI experts, but they have to talk to the AI experts. They need to have an open-minded interdisciplinary conversation around what types of data that a machine learning system would need to use in order to detect fraud.

Someone who works in fraud might be able to tell the artificial intelligence data science talent what kinds of data is most important here. For example, they might put a lot of emphasis on the IP address, the location of the user. That might be something that's weighted very highly when it comes to things that correlate to fraud.

They might be able to let the data science folks know some other category of data. For example, maybe when it comes to behavior within a mobile app they might know historically the kinds of behaviors that correlated more likely to fraud over the last two or three years.

Sometimes the feature engineering phase ends with the conclusion that companies currently don't have the data to train a machine learning system or that the company does have the data but rebuilding the data infrastructure in order to make that data accessible right now is cost-prohibitive given the potential ROI that the company could get from this product or project.

Our third installment in this guide is going to be about underestimating the time to value. In other words, why is it so much harder than with run of the mill IT to estimate when an AI system is going to start paying for itself?

Insight 3 - The Difficulty of Predicting the ROI of AI

There are a lot of misconceptions running rampant around the ability to gauge the return on investment of artificial intelligence. This section explores what can and can't be done when it comes to investing in artificial intelligence and predicting what the return might be.

- How much will an AI project cost?
- How long will the integration take before the software is ready to use?
- How will it be able to be used to drive value?
- Does it solve the problem it was initially supposed to?

None of these questions are easy to answer. This section lays out exactly why this is and goes into some of the critical reasons why it's very hard to gauge the cost of an AI project, the time to completion for an AI project, and whether or not the project is going to work out.

Common Delays and Challenges

The subject-matter experts and data scientists at the company could all agree that AI is right for the company, but if there is no way of telling how long it will take to clean, organize, and harmonize the data so that it can be fed it into the system and train the AI, this could still be a problem.

Once the data infrastructure is in place, now the model must be trained. Once a company begins training models, that company has to see if the AI is generating a potentially better recommendation than it was before. The only way to test those recommendations might be to expose them to our customers and with that comes the need to measure the response appropriately.

Companies can also experience issues with training the algorithm, seeing if previously collected data is even capable of being able to train their algorithm in the first place, and it may not. Companies may spend six months trying to train different algorithms with the kind of data that was collected and realize, upon completion, it's not better than the previous status quo.

A lot of AI applications will interact with customers, and these happen to be the most challenging to bring to life for a variety of different reasons. One of these reasons is the low percentage of AI talent at a company, data scientists, machine learning engineers, that have actually built AI software that have been deployed in business. This is rare.

In addition, how does a company new to AI measure the results of their AI product? Even structuring the assessment of measurement is a challenge.

Up to this point, it may sound like artificial intelligence is a poor investment. If returns can't gauged, if projects are going to take longer than companies think and there are so many points of failure, why would companies invest in artificial intelligence in the first place?

To be frank, that's a very good question. Right now, most midsize companies with absolutely no data science savvy probably should not be investing very much in artificial intelligence.

If a company can't predict how artificial intelligence is going to produce a return on investment for itself, what kind of ROI considerations can be made? What can the boardroom and the C-suite actually be doing when it comes to thinking about AI ROI?

There are two things that they can do.

Discovering the Landscape of AI Applications in a Sector

Companies new to AI may not be able to know the ROI of individual use cases, but what they can know is the landscape of AI applications in a sector.

If a banking executive only reads banking press releases before they spend money with AI vendors, they are inevitably going to be investing in the wrong places. It makes sense to get a deep understanding of where a return on investment is being garnered with AI in a sector.

In addition, it's worthwhile for companies to consider what core AI capabilities are in their sector and how those capabilities overlap with their company strategy. For example, a data scientist at Staples told me the other day that Staples is focusing right now on recommendations. They're re-imagining their business in the era of Amazon, and recommendations is a very big priority for them.

If that's the case, it's worth understanding which facets of recommendations within the world of eCommerce and brick-and-mortar retail are actually garnering a return.

Companies can go out into the world of AI and find capabilities and applications that plug into their recently discovered and uncovered ideas. Even though a company might not know what the return is going to be, at least they are aligning technologies that can be assumed to work from robust research in the space with existing company strategies. This benchmarking is not going to steer them off course.

Concluding Thoughts

In order to achieve success with AI, companies need to grasp what the AI capability space in their sector actually is.

General business infrastructure does not allow for the kind of iteration, testing, and experimenting that AI requires. Instead, enterprises can think about AI adoption with a venture capital analogy.

Think about a venture capital firm managing their returns; they're not looking at a "to-the-penny" assessment and a "to-the-day" assessment of how much and when a certain return happens. Instead, they're making informed bets. They have a strategy. They decided to invest money in different parts, presuming some of them could really explode and become very high capability investments.

Instead of looking at each individual project as something that needs to project an ROI, instead, manage a fund. A fund within an enterprise can roll the dice on a number of different projects. Again, they shouldn't be picking random projects. They are doing them in line with their strategy, but selecting a number of them and then looking at the return of the whole fund as opposed to individual projects.

It's important for companies to understand their desired outcomes in their current business strategy and to mesh their strengths and priorities with the capabilities of AI that actually are showing real promise. This is the most likely stratagem to give existing enterprises a leg up as AI becomes more accessible and starts defining the winners and losers in different industries.

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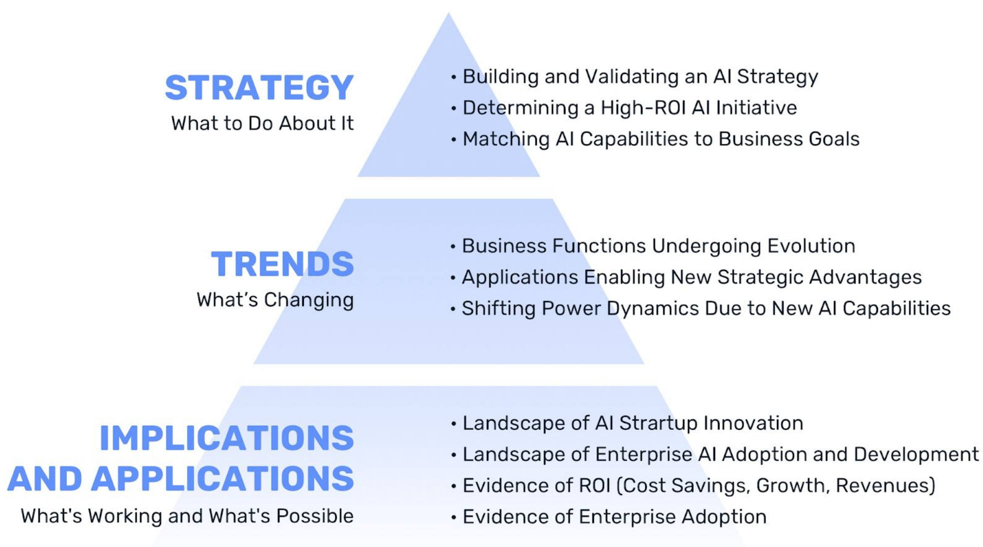

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