*Executive Insight*
Business Fit Assessment

FREEFORM DYNAMICS

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FUJITSU

# AI in Industry: The Myths and Reality

## Machine Learning as a key enabler of next-generation industry

Freeform Dynamics, 2020

# Introduction

AI - or Artificial Intelligence – has been one of the most talked-about technology topics of recent years. Sometimes it is portrayed as a threat, at other times it is hype: fantasies of intelligent androids have created a marketing frenzy. Many IT vendors and service providers have tried to put an AI spin on their offerings, even if in some cases the reality was merely a rule-based workflow engine with a fresh coat of paint.

Then again, most of what we read or hear about AI is actually about something conceptually far simpler: Machine Learning, or ML. This is a subset of AI, but it is a long, long way from intelligent computers and the like. ML merely uses mathematical and statistical models to make automated predictions and inferences from data.

Admittedly, they can be extremely complex models, and there are well-publicized risks in building those models on human decision-making or on personal data. However, things are rather different once we move into predictive maintenance, supply chain optimization, quality control or one of a host of other industrial areas. AI techniques, such as ML and its multi-layered subset Deep Learning (DL), have the potential to make dramatically faster and more accurate decisions here, based on far more data than a human could absorb.

It seems clear that AI is essential, therefore, to the continued digitalization of industry - to Industry 4.0 and what comes after it. With that in mind, this paper will look at the myths and realities of AI, and at what you need to know and ask when assessing and/or implementing it in an industrial context.

With the help of a survey, we have examined how organizations currently use or plan to use AI, and we will consider an example from Fujitsu, the sponsor of this paper, of how the focused and domain-specific use of DL – such as for quality control via automated image recognition - has the potential to deliver measurable and serious business ROI.

# Hope versus hype

Given its portrayal in Western fiction and popular media, it is no surprise to find widespread skepticism regarding both the readiness of AI technology for mainstream enterprise deployment and the business case for investment. Indeed, many of the survey's 192 IT professionals mentioned a weariness with the noise:

*"It's hype and not ready for prime time."*

*"AI is such an overused buzzword that it is hard to see through all the marketing claims."*

*"I see a lack of robust business cases."*

*"The real value of systems is being lost in all of the Skynet discussions."*

That last comment, with its reference to the murderous computers of the *Terminator* films, illustrates the ambiguity that is such a challenge for those looking to AI for real business value. On the one hand, the term is used in the movies to describe machines that threaten human existence, while on the other it is exploited to rebrand familiar IT automation tools to make them sound more modern. Even in between, confusion often arises from a lack of clarity and consistency:

> *"AI seems to include a whole spectrum of ideas and capabilities, and everyone seems to differ on what it includes or means."*

The truth is that it is almost impossible to generalize when it comes to AI. First, there are cultural and social issues. Then you need to be specific about the technologies, use cases and applications being discussed before you can make an assessment of the business value or mainstream readiness. Sure, some forms of AI are immature, even still largely experimental. However, machine learning principles and technologies are now well-proven in other areas, where they have already brought significant business and industrial advantage.

But before we get into the roles and practicalities of modern AI platforms, let's look at the research we mentioned above, as it provides some useful context for the discussion.

# Growing understanding of the AI imperative

Our AI survey was conducted online in Q2 2019. It covered a cross-section of geographies, organization sizes and industries, with a bias towards respondents with a particular interest in manufacturing solutions (41% of the sample). Overall, we picked up different levels of appreciation for the role of AI in helping to achieve the key business imperatives of market competitiveness and operational efficiency (Figure 1).

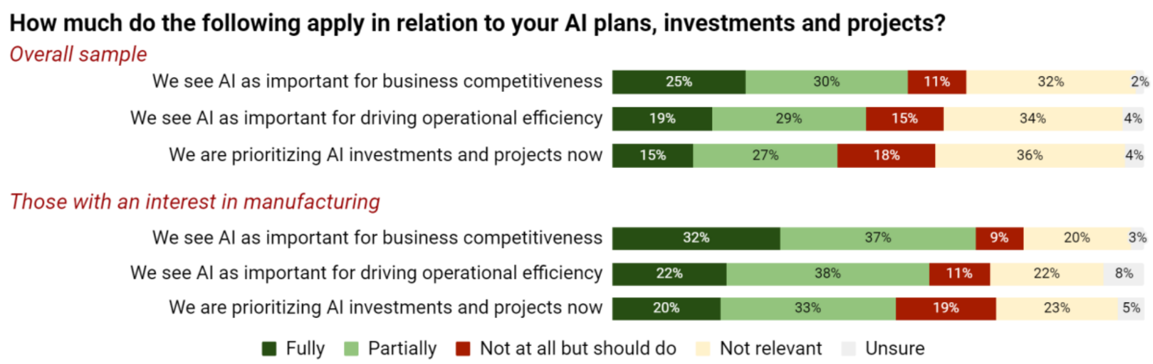


*Figure 1 The priority accorded to AI investment does not match its importance*

Worth noting on the above chart is a suggestion that the AI opportunity is generally well-appreciated within manufacturing. This is most probably connected to this sector's historical focus on automation, and the potential for AI solutions to help take this to another level of efficiency and effectiveness.

That said, only a minority of organizations have completely bought into the AI proposition at the moment. It is a significant minority though, and it is interesting to note that around one-fifth of respondents say their organization is failing to properly prioritize AI.

# The diversity of AI solutions

Picking up on an earlier point about the difficulty of generalizing across the broad range of AI opportunities, our research indicates that activity is already underway in many application areas (Figure 2).

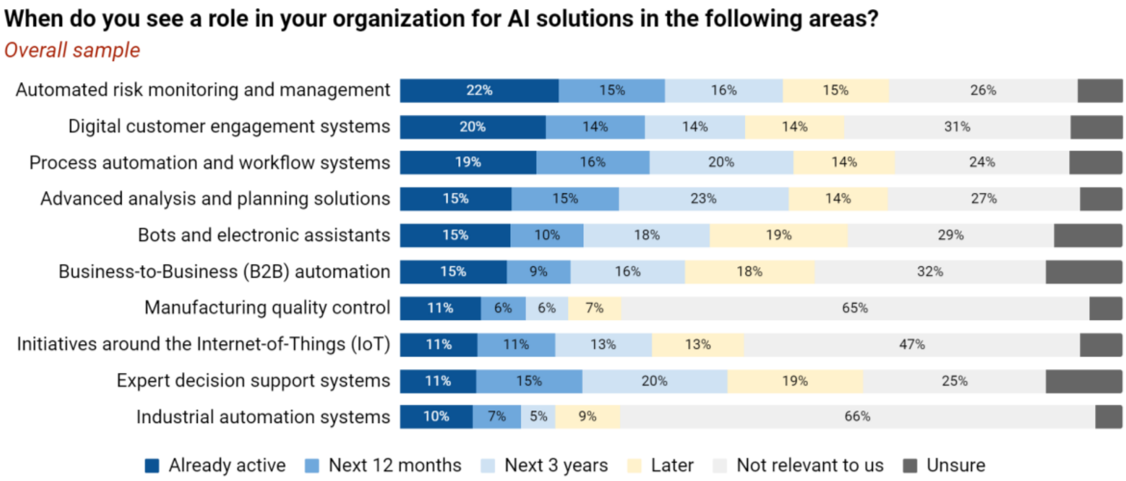


*Figure 2 Activity is underway or on the agenda across a wide range of application categories*

Again we see quite a bit of variation in responses, which confirms that some organizations are much further along their AI journey than others.

At first glance, you might think that the items towards the bottom of the list represent weaker propositions compared to the ones above them, but the picture presented in Figure 2 doesn't take into account the significant variation between industry sectors. When we break out those with an interest in manufacturing, for instance, a different picture emerges.

## Spotlight on Manufacturing

We see higher levels of activity when we focus on respondents with an interest in manufacturing and home in on solutions that are more likely to be relevant in an industrial or supply chain context. In addition, more respondents report that they have both short and medium-term plans for AI investments and projects (Figure 3).

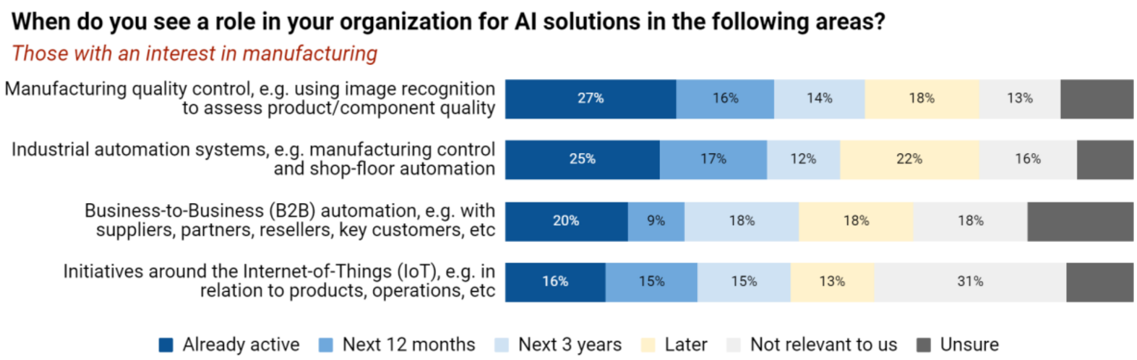


*Figure 3 The opportunity in manufacturing is clear in relation to key application categories*

The shorter list here is a subset of the one in Figure 2, but in this version, we have both focused on respondents involved in manufacturing and provided the expanded descriptions of the application categories that were used in the survey. This gives a better feel for the specific propositions being considered.

The category at the top of the list - quality control, typically shortened to QC - may surprise some, but it makes absolute sense if you are familiar with both the key priorities and imperatives of industry, and the bottlenecks that it still faces. QC has traditionally been one of the few areas that could not readily be automated, and which as a result still relied heavily on manual inspections.

# Overcoming the many hurdles to AI adoption

Although AI activity is underway in many industrial areas, there is also significant uncertainty associated with AI platforms and their implementation. Simply knowing what to expect and how and where to start were reported as major challenges by significant numbers of survey respondents. Other key concerns include the AI skills shortage and the challenges of securing, maintaining and evolving an AI platform in everyday use (Figure 4).

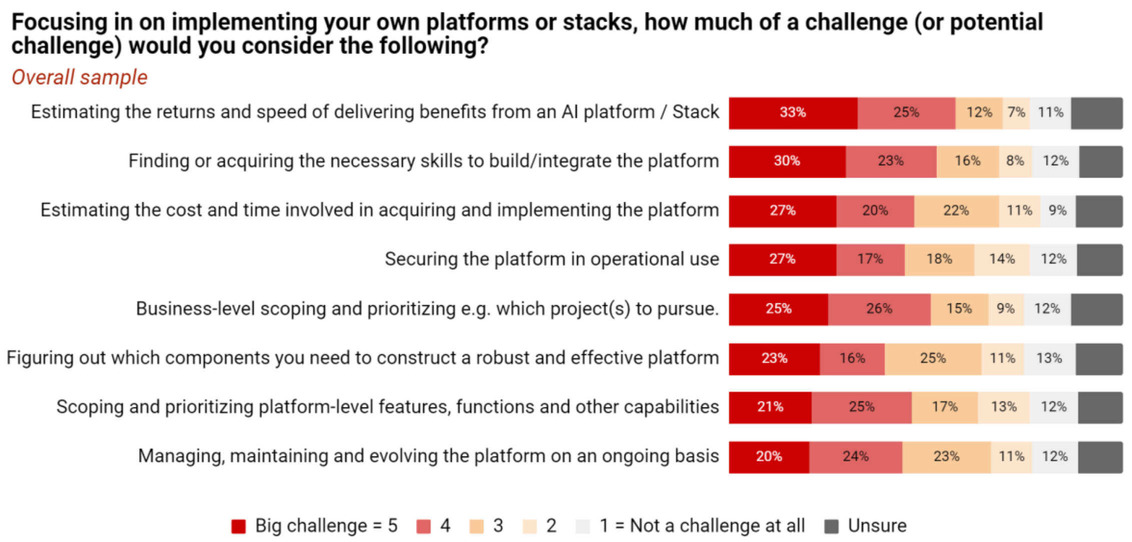


*Figure 4 Unfamiliarity with AI and its relative novelty present challenges for many*

This uncertainty is an area where suppliers and service providers who already possess AI expertise can do a lot to help, both in terms of de-risking and streamlining adoption. It is not surprising therefore that our survey respondents saw considerable appeal in generic platforms, reference architectures, pre-integrated systems and so on (Figure 5).

 

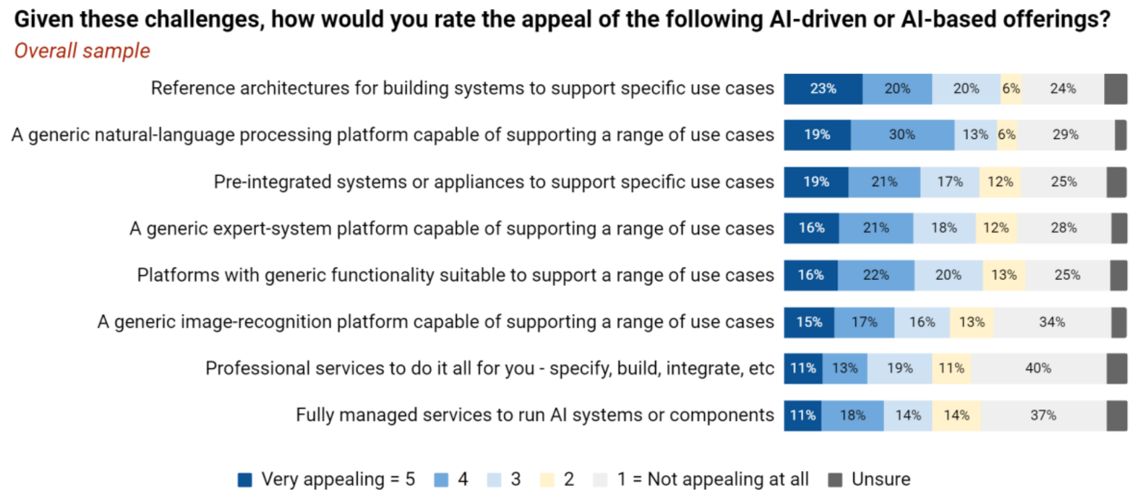


*Figure 5 Reference architectures, appliances and platform approaches appeal to many*

One interpretation of these findings is that respondents like the idea of offloading concerns such as which components and platform features you need, and the issues of security and maintenance, onto a purpose-designed AI technology solution. This platform route also has the potential to shorten the timescales involved, make costing and planning more transparent, and reduce both the operational overhead and the requirement for specialist AI skills.

The opportunity for such packaged or pre-planned AI solutions, in particular for pre-integrated systems and reference architectures, is even more evident when we focus on respondents with a manufacturing interest (Figure 6).

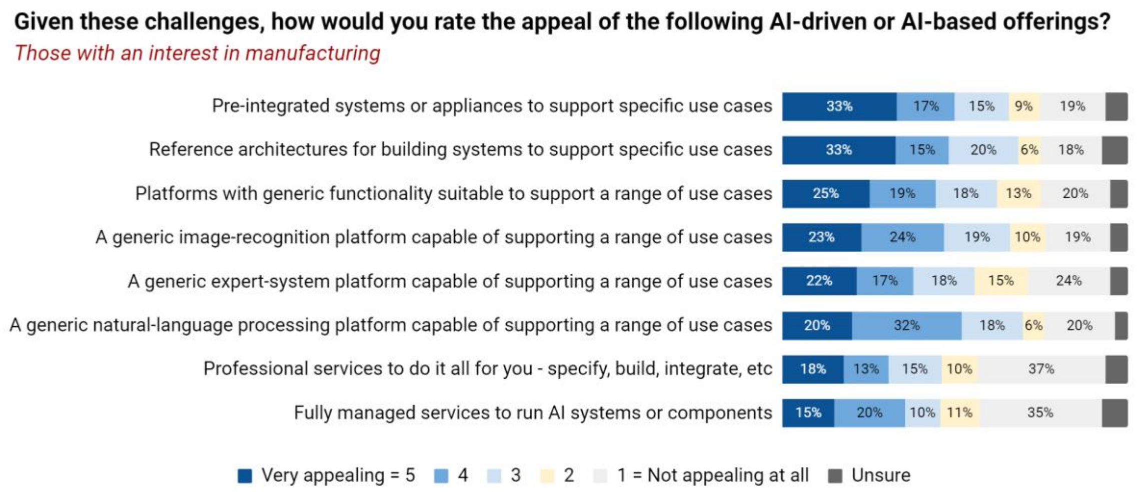


*Figure 6 Packaged AI approaches are popular in manufacturing*

Why would the industrial sector see more appeal than the average in approaches such as reference architectures and appliances? The answer may lie in the engineering and industrial mindset: if you have a requirement or challenge and a tool or proven design exists to deal with that, and you can get the funding and demonstrate ROI, you buy or build that tool or proven design and put it to work.

### The need for teamwork

One last hurdle that may not be seen until the project is well underway is that AI is very much a multidisciplinary team activity. However, while our survey respondents say that AI projects can be driven by different groups within an organization, more than a third of them report that people do not always pull together as well as they should (Figure 7).

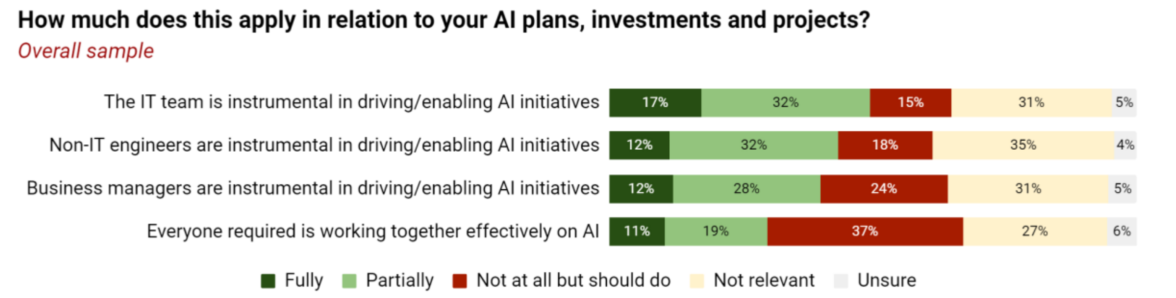


*Figure 7 Success in AI requires a coordinated multidisciplinary effort*

Why might this be? In some cases, it may be that not everyone who needs to be involved is actively involved in practice. In others, the team's effectiveness might be reduced by factors such as internal politics, shortage of time or other resources, or lack of senior commitment. Whatever the challenges, it is essential with AI to get teams working together across boundaries, because technologies such as ML and DL require input and support from all the affected areas of the business, not just from IT.

## The industrial implementation of AI

Any implementation of machine learning-based AI is going to be a complex task, requiring extensive domain expertise both in ML and in the specific field it is being applied to. Manufacturing has advantages here, because it is grounded in measurable, testable and repeatable engineering, not in a hard-to-quantify science such as psychology.

For example, we would expect that a QC inspector's decisions are unlikely to be influenced by subjective factors or assumptions - or at least, for the inspector's assumptions to be based on past technical evidence. In contrast, numerous studies have shown that AI can repeat and even amplify the inconsistency and bias present in human decision-making, unless its training data is carefully reviewed and validated.

### AI platforms

In addition, those involved in manufacturing are often the ones most keenly aware of the opportunities offered by machine learning and deep learning. As we saw earlier, while manufacturing and production engineers are unlikely to have the specific skills and expertise needed to build such systems, they can acquire purpose-designed AI technology in the form of pre-configured appliances, reference architectures and so on.

These typically contain the complete stack needed to support ML and/or DL solutions, from hardware, through system software and middleware, to analytical frameworks and models that provide core AI functionality.

The question is whether those engineers (and others involved in manufacturing) are sufficiently aware of the availability of packaged AI technology and the opportunities it offers. The results of our study suggest that many of them are not.

## Delivery options

There are many ways to deliver and consume AI capabilities. They include public cloud services addressed via APIs, dedicated ML and DL software stacks running locally or on a hosted service, ML features embedded within SaaS applications or hardware devices, and several other hardware/software combinations in between.

To complicate matters, different delivery options can be more or less relevant at different stages of the AI process. For example, training an ML system is far more resource-intensive than inferencing, which is the routine application of the trained model to a production process. In addition, training typically must be repeated periodically, or even continuously, based on feedback from the inferencing process and as the tools, models and processes evolve.

There are other factors to consider, too. For example, delivery options such as public cloud-based AI platforms and discrete AI functions hosted in public clouds are broadly relevant. However, the lower latency of on-prem and private hosting will be more relevant in some manufacturing applications, where a faster and more consistent response is required (Figure 8).

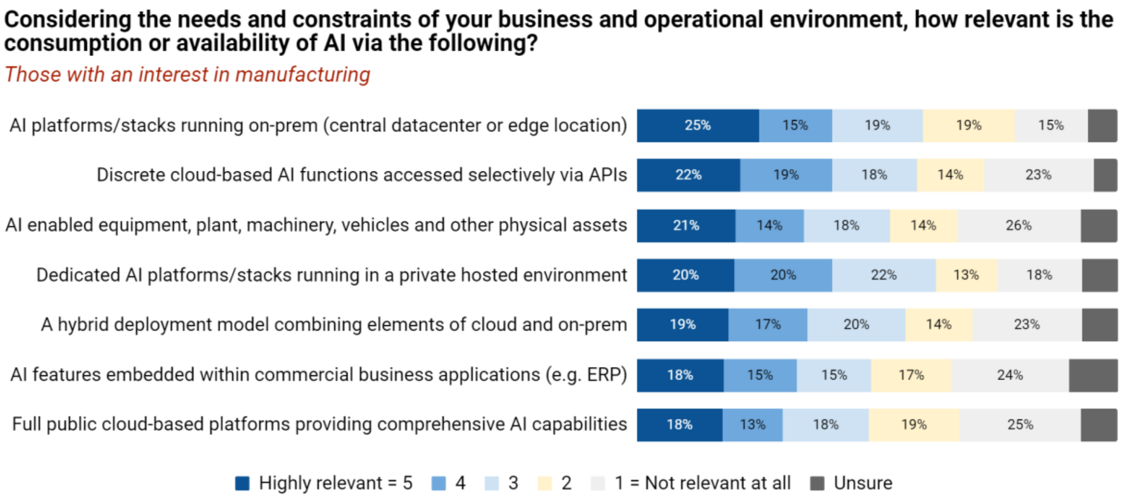


*Figure 8 There is a wide range of delivery options*

## Engineers in the driving seat

Not too surprisingly, we find that in manufacturing contexts, non-IT engineers have a greater role in driving and enabling AI plans and projects. In some cases, however, they are not as involved as they ought to be. Whether this is due to skepticism, lack of time or simply to a lack of awareness, it seems clear that while many industrial engineers, production engineers and others readily recognize the opportunities offered by AI, this is not true for all engineers in every organization (Figure 9).

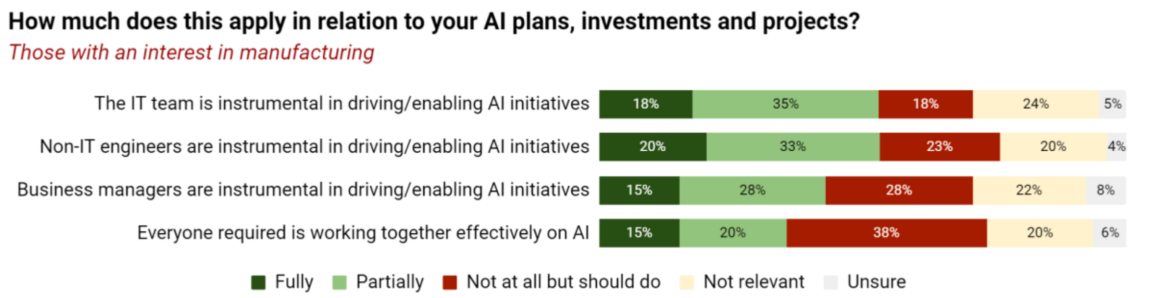


***Figure 9 AI is becoming an engineering tool as much as a business one***

# Example: Fujitsu's data-driven AI implementation

As an example of a flexible way to implement AI, we will use the reference architecture for data-driven deep learning solutions from Fujitsu, the sponsor of this paper. While nothing we say here should be interpreted as an endorsement or recommendation of Fujitsu, specific examples enable us to move beyond the theory, and illustrate how some of the key principles we have been discussing can be translated into operational reality.

For instance, this reference architecture allows DL to be integrated into a wide range of processes – use cases so far include a predictive maintenance system for helicopter flight testing, a non-destructive testing system to detect anomalies in aircraft components, and a 'solver' which predicts principal fluid flow distributions within an arbitrary 3D space.

To dig into the industrial potential for deep learning, let's take the example of automating visual inspection in quality control, or QC. In recent years, other areas of manufacturing have seen increasing levels of automation, but inspection for QC has proved harder to automate. As a result, in many industries inspectors comprise a significant proportion of the manufacturing workforce, and an increasing fraction of the production process time.

## Easing the inspection bottleneck

One of the challenges for quality control is that while humans can be very good at spotting visual differences or errors, for example in a component or finished product, they get tired. There is also a physical limit to how rapidly the human eye can fix and focus on each new sample as it comes along. A common workaround is random sampling, but that can never be as effective as thoroughly checking every unit.

The idea of using machine vision to assist humans is not a new one, but it is significant when we talk about 'human-centric AI' - the concept of using AI to help humans work better and faster, rather than to replace them. For example, in the case of QC, the ability of AI to work with probabilities would allow it to perform triage: a trained AI would be able to definitively pass or reject most items, based on set confidence levels, while highlighting those it is unsure about for expert human inspection.

 

In addition, because you 'teach' the AI either what a defect looks like, or for unsupervised techniques, what normal looks like, it does not matter how you produce the image or scan. Indeed, it does not even have to start out as an image - converting other data into a graphical form allows deep learning algorithms called neural networks to spot discrepancies that are invisible to the human eye.

## Simplifying the integration

Automated optical inspection is already well established in areas such as the high-volume manufacture of printed circuit boards. However, it has typically been relatively complex and expensive to deploy. It requires specific set-up and programming for each product or component to be checked, and there is also the question of how to integrate other inspection methods such as ultrasonic or x-ray scans.

This is where Fujitsu's human-centric AI reference architecture comes in. It provides a tested 'recipe': it lists the necessary components such as platforms for edge, core and cloud, workload management, the AI frameworks and the business interface, along with how to build them into a viable solution. This can then be collaboratively sized and configured to fit the customer's ecosystem and needs, making it simpler to integrate AI with existing operational systems. In addition, Fujitsu brings expertise that can greatly simplify the process of choosing the right algorithms (frameworks) for the task at hand and then getting the DL system up and running (Figure 10).

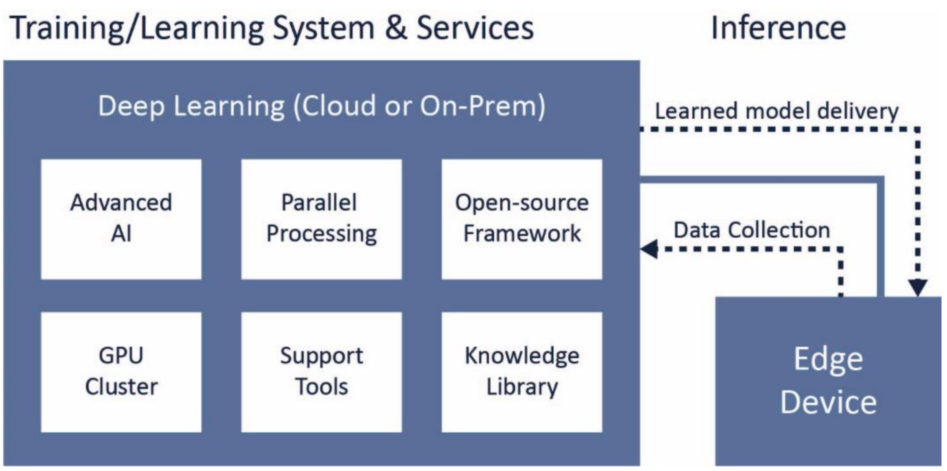


*Figure 10 A complete AI/ML stack includes many elements and a feedback loop*

## Implementation and deployment

As we saw in our study, respondents in manufacturing lean towards having their AI on-premise - or at least the real-time inferencing element of it, with its need for low latency and availability. However, they anticipate significant challenges in scoping, costing, building and securely implementing such systems. This may well be because they recognize, but do not know how to cope with, the complexity created when the key elements of the task - training and inference - have notably different workload profiles.

End-to-end solutions based on data-driven techniques and a reference architecture can deal with these issues via software models tailored to the local operational environment and the task at hand. For example, a solution optimized for deep learning should provide the power needed for training the AI. Once it goes into service, the workload becomes real-time inference, and the key performance metric is latency, not compute power. In some use-cases an edge device with an Intel scalable processor will be sufficient for this, while other cases might require AI acceleration hardware such as an Nvidia GPU.

This relatively standardized approach, with a reference architecture, can make physical integration and deployment easier to do. Similarly, it can be a significant advantage to work with a supplier that has expertise in AI technology, algorithms and intellectual property, and which also has experience in data-driven manufacturing, the selection and integration of relevant devices such as cameras and scanners, and the storage and organization of their acquired data.

# In conclusion: With AI, one thing leads to another

The survey results appear to indicate that, when it comes to AI, uptake and acceptance are infectious. In other words, once you recognize the potential via one project, you are likely to see the opportunities for broader AI usage across the organization (Figure 11).

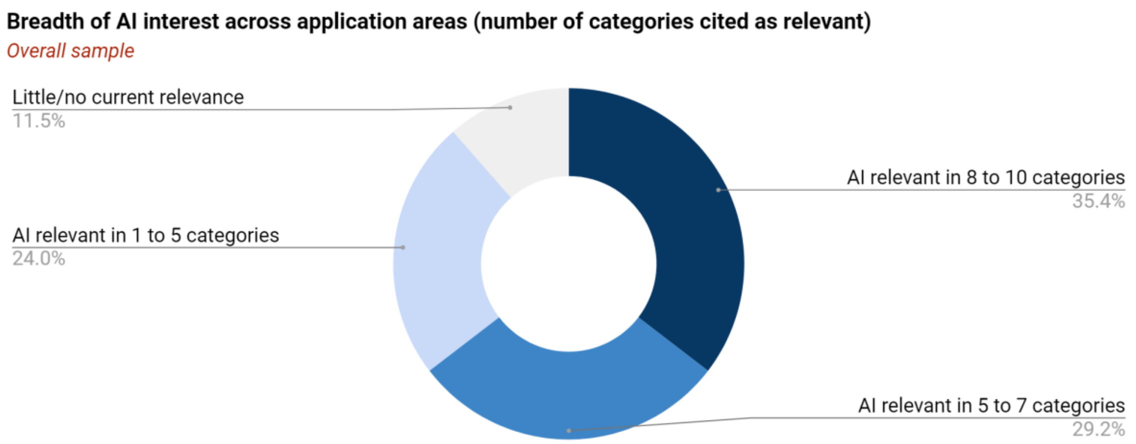


*Figure 11 AI is both broadly relevant and of broad interest*

The most important thing will be to get that first AI project up and running. A number of things can help here. First, find an application area that offers a quick win with obvious positive and measurable results. For example, this might be an area where automation offers significant benefits but has previously been infeasible or not cost-effective.

Second, involve your workforce as early as possible, using AI to help the people to work better and faster. Not only can this improve their cooperation, it should also yield better results overall, as you leverage the strengths of both your people and the AI.

Next, packaged and semi-packaged AI platforms may enable faster and easier implementation and reduce many of the risks involved in new technology. And lastly, work with a supplier that understands both AI and how your industry operates, and who can help you keep it running 24 by 7, worldwide.

 

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