# How to Create an AI Center of Excellence for Enterprise

Lead business and technology expertise within your organization to deliver on artificial intelligence that drives revenue, customer experience, and more, powered by high-quality training data.

An Appen eBook

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# Introduction

Organizations are beginning to invest heavily in artificial intelligence (AI) initiatives. Some are spending millions of dollars on AI strategies, and with good reason. Companies that have already adopted AI report that it has allowed them to edge ahead of competitors.

If you're reading this, chances are your organization has already made inroads on an AI strategy. You may have one project under your belt but find yourself asking, "Now what?" The first thing to remember is patience. According to Gartner's senior director analyst Chirag Dekate, "Delivering business impact from AI initiatives takes much longer than anticipated."

Remembering that it will take some time before realizing a return on your AI investment is crucial, as well as acknowledging the fact that you'll need buy-in from other stakeholders of the value of AI.

To convince stakeholders to embark upon AI journeys, you must find and attract internal customers for artificial intelligence. These individuals or teams are interested in AI, but probably aren't sure where to begin.

Whether they know it or not, these stakeholders' journeys begin with training data. Training data is crucial to AI. In fact, AI can't exist without high-quality training data. You need to develop a resilient data fabric in order to collect, store, and annotate data that will be used to train machine learning models.

**AI will be used by 40% of Infrastructure and Operations teams by 2023**

(Source: Gartner)

## What is the best way to ensure your machine learning is accurate in production?

**Build a training data practice in your AI center of excellence (CoE), as part of your resilient data fabric**

**Definition:** Data Fabric
Data fabric enables frictionless access and sharing of data in a distributed data environment. It enables a single and consistent data management framework, which allows seamless data access and processing by design across otherwise siloed storage.

According to Gartner, through 2022, bespoke data fabric designs will be deployed primarily as a static infrastructure, forcing organizations into a new wave of cost to completely re-design for more dynamic data mesh approaches.

Learn More

# What Is a Center of Excellence?

## Some organizations have it, some are still getting around to building it. It's important to define a Center of Excellence.

**Definition:** Center of Excellence
Team of people that serves as the nexus of expertise for a given field of study or subject.

The concept of a center of excellence (CoE) has been around for a while. This team manages resources, provides counsel, and offers best practices for any other team or individual that wishes to learn more about the CoE's given subject. Firms in many industries have already developed their own centers of excellence, which can provide a blueprint for organizations that wish to develop their own centers.

- The **Infosys automation CoE** was built using a "detailed process analysis for automation suitability and adopted a hybrid delivery model" that has improved efficiencies between 30% and 80%.
- Microsoft has a **Data Insights Center of Excellence** and offers its services and technology to organizations that wish to establish their own CoE.
- NTT Data has an **AI center of excellence**, geared toward developing "further expertise in AI and train[ing] engineers engaged worldwide in the AI field."

Services organizations, such as **Forrester** and **McKinsey** offer advice on how clients can develop CoEs for any number of purposes.

While the purpose of CoEs runs the gamut, AI and its related fields are arenas where centers can produce plenty of competitive edge. AI has become so important to modern organizations that **more than one-third** of large firms, including non-technology firms, have already established a CoE for the explicit purpose of furthering AI.

Thomas Davenport, an MIT Digital Economy research fellow, professor at Babson College, and senior adviser at Deloitte Analytics, and a senior adviser at Deloitte Analytics; and Shivaji Dasgupta, Managing Director and Head of Data Architecture and Smart Analytics for Deutsche Bank's Private and Commercial Bank, provide, via **Harvard Business Review**, guidelines for establishing a CoE.

- Create a vision for AI in the company
- Identify business-driven use cases
- Determine the appropriate level of ambition
- Create a target data architecture
- Develop and maintain a network of AI champions
- Spread success stories

While the specifics of the organizations' approaches differ, the basic direction is similar:

## Building the AI Center of Excellence

Make the Case for AI in your Organization → Get Executive Buy-In for the AI CoE → Build your CoE Team & Architecture → Launch your Initiative By Building a Flywheel

# Make the Case for AI in your Organization

## Identify the key business and customer use cases, the data you have, the data you need, and establish the scope of your AI Center of Excellence

To identify the first issue to tackle with your CoE, it's better to think of the exercise as one of discovery. Discovery is a process best approached through questioning and iterating. The end goal is to best understand how the CoE can act as a go-to resource for any machine learning-related questions the company has.

There will be many internal stakeholders with whom to meet — such as: Data Science, Product, Engineering, Professional Services, Customer Service, Success, and Business Development leadership. The individuals and teams whom you consult as part of the discovery process will change from organization to organization. However, it's important to meet with product teams to understand their roadmaps; engineering teams to uncover their efficiency issues; data science teams to uncover available data, and customer success teams, as they'll be attuned to what customers need and want out of your products.

With a strong grasp of various internal roadmaps and who owns their direction, there's a much greater chance you'll identify where your company's data challenges exist. Now it's time to think about executive buy-in.

# Get Executive Buy-In for the AI CoE

## Team effort both operationally, and strategically, gets AI executed at scale

Getting executive buy-in early is the key to getting an AI initiative kicked off the ground. Demonstrating your project's effectiveness can help you build the business case for a CoE and also **establish credibility** for AI as a useful tool. Here, it's important to remember that you're not building a business case for just one specific problem or problems.

You're focused instead on showing how AI can scale to positively impact many facets of your business. The fact is, **making the shift** to an AI-powered organization (which is the ostensible goal of creating a CoE in the first place) requires building an infrastructure that can support interdisciplinary functions.

In many cases, someone like the CTO or VP of Engineering or Product is responsible for AI initiatives, given that it usually leverages both engineering and data resources, for training and deployment. Part of securing buy-in will be affirming that the CTO or other technology leader is willing to lead the CoE team.

If, rather than a product leader, line-of-business owner, or technical practitioner, you are the CTO or executive responsible for a CoE, then it is imperative you prioritize this initiative, fuel it with relevant and sufficient data, and build the right team, and the right infrastructure, to deliver on the AI goals.

Provectus

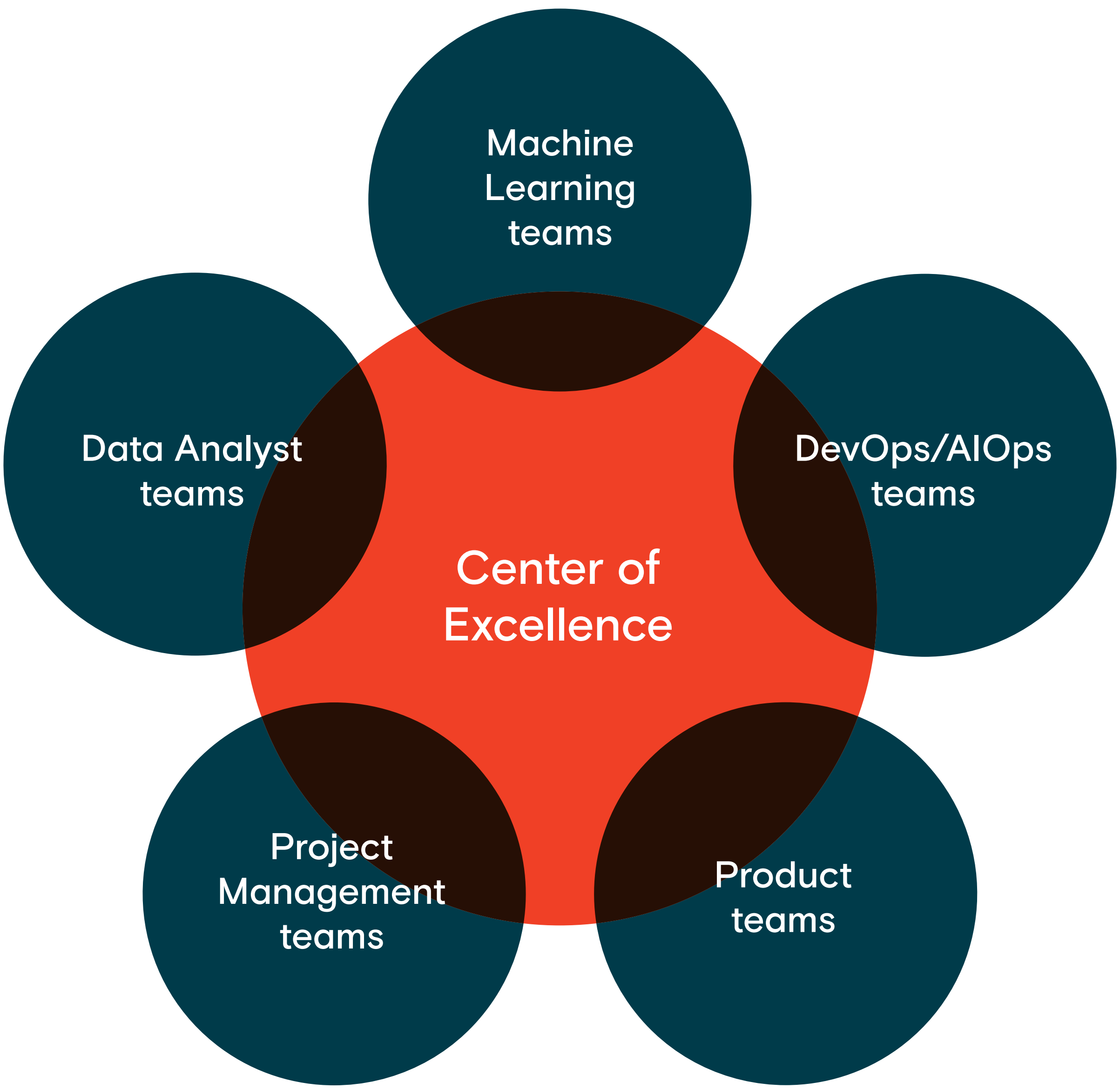
Artificial Intelligence consultancy and solutions provider

> "An AI CoE can significantly improve the likelihood of AI providing true value back to the business by introducing standardization of tools, data architectures, processes, and knowledge sharing. It ensures day 1 value focus by enforcing the identification of measurable KPIs and success criteria in early stage PoCs. The CoE, combined with the best of breed tools, like Appen's platform, enable different business units to securing quick wins and create massive momentum across the organization for AI programs."

PAT MCDERMOTT, HEAD OF STRATEGY & BUSINESS DEVELOPMENT AT PROVECTUS

# Build your CoE Team & Architecture

## Under the CTO, most AI CoE teams will likely look similar to the following composition



# AI CoE Teams

## Machine Learning

Machine learning teams are specialized and built to help improve the processes that support the core of the business. Typically, data scientists and machine learning engineers make up the bulk of the team.

Data scientists are often responsible for creating new data architectures to solve a given business problem. These team members are typically up to date on the latest technologies and how to best leverage them. Scientists also often help engineers troubleshoot the ML model.

ML engineers understand which type of architecture they need to build and train the model or series of models. They should be well-versed in working with different data types, testing and tuning the model, and figuring out how to get the model into production. Furthermore, engineers help make sure the entire pipeline can support rapid development and iterative increments after launch.

Despite the fact data scientists and ML engineers are up to date about the latest industry trends and technologies, their primary focus is on the data itself, rather than R&D-type activities. Identifying the appropriate data to use, ingesting that data, and cleaning and annotating it are crucial to building a successful model, and our research suggests most data scientists spend at least one-quarter of their time managing, cleaning, and/or labeling data.

While research projects may be more appealing for their excitement, the current truth is that much of a technical practitioner's job is in the more tedious production work.

## Data Analyst

Data Analyst teams use business intelligence (BI) tools to understand data's impact, unlike data scientists, who focus on building and explore algorithms. Both data scientists and data analysts can be data mungers, who work with the data on their own to identify issues and devise strategies to fix them, either internally or with trusted vendors.

aws

**Amazon's mission is "to be Earth's most customer-centric company"**

> "We believe that machine learning leaders have the opportunity and responsibility to leverage the latest advancements in AI technology to deliver a step-change improvement in customer experience. Appen provides the required collaboration between technologists and business leaders to solve vexing challenges and embrace ambitious opportunities. Through our partnership, we are striving to offer the best selection to our customers with high-quality training data at the core of their initiatives."

KRISTOF SCHUM, GLOBAL SEGMENT LEADER OF MACHINE LEARNING IN AWS PARTNER NETWORK

# AI CoE Teams

## DevOps

DevOps teams ensure everything runs smoothly on the company's infrastructure. Organizations need DevOps support to launch a model and manage the continuous delivery pipeline. DevOps also helps the team understand if the model is working as intended, as well as oversees and maintains the technology behind deploying the model. date on the latest technologies and how to best leverage them. Scientists also often help engineers troubleshoot the ML model.

## Project Management

A technical project manager liaises between the product team and engineers, data scientists, and DevOps teams. They manage the entire process and evaluate and curate the tools the team uses. This role should be filled by someone who is able to lead those conversations and understand the requirements of the product side to figure out feasibility and, just as importantly, prevent the model creation from getting too research-oriented or too costly.

## Engineering

Engineers can and often do interact with DevOps engineers, but you want to make sure the interface between the ML team and traditional departments is seamless. For example, maybe a mobile app is talking to the model, but it wasn't previously — you need the right people in place to make sure the API is integrated and working.

If your organization uses a cloud infrastructure provider, such as Amazon Web Services, Google Cloud, or Microsoft Azure, then it may also invest in a cloud infrastructure manager who is an expert in whichever data lake the company uses.

## Product Management

Product managers bring in the ability to understand the workflow in terms of how it's affecting the business case and how it's making money. They are a critical part of the CoE group, especially for product-first organizations, where AI can become a key part in delivering business value.

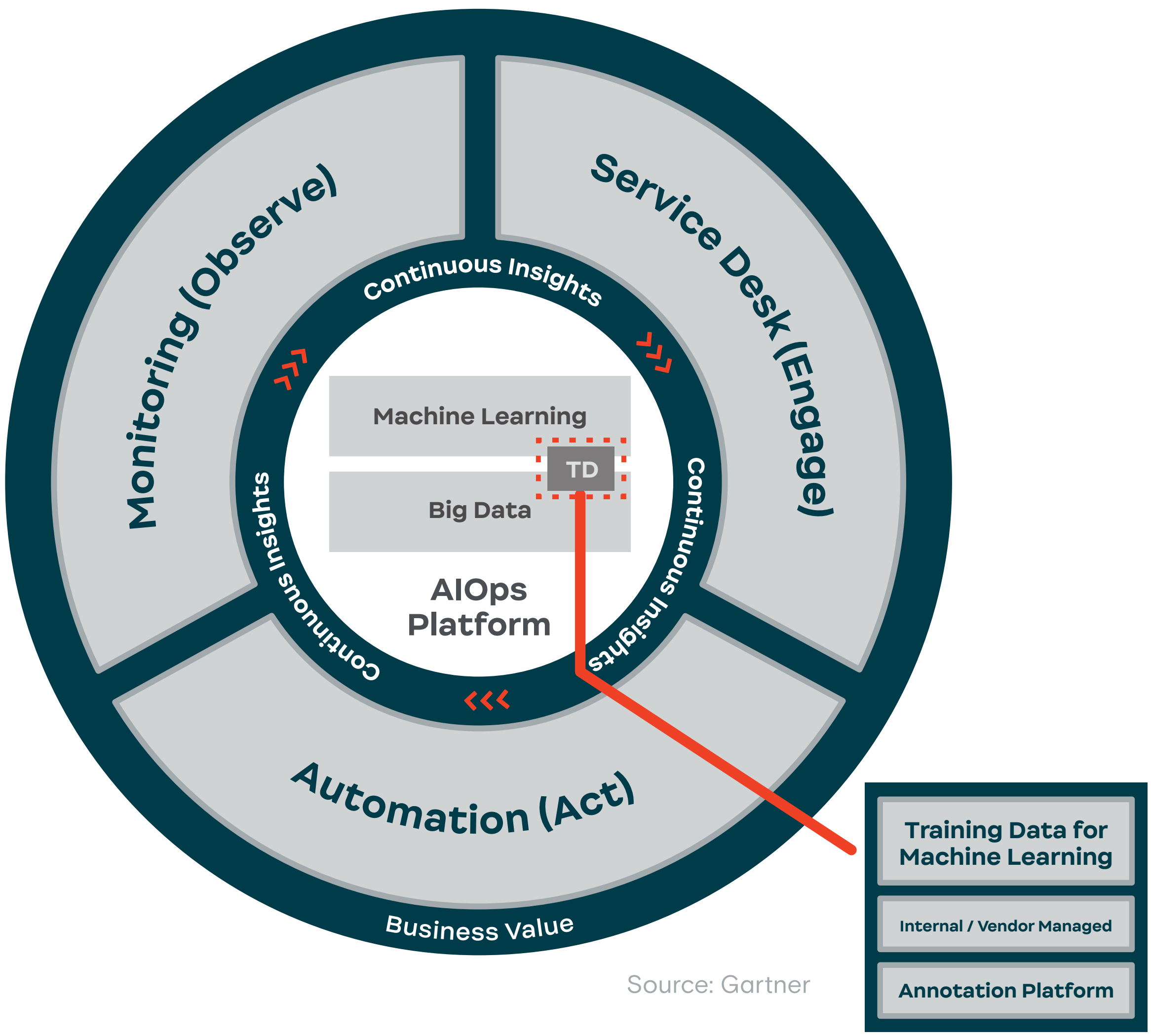
The product manager should also have expertise in the specific space in which the company is developing algorithms. A large part of a scientist's time is spent in only one field because the speed at which various forms of AI-enabling techniques, like deep learning or computer vision, are evolving requires them to specialize. Accuracy for video is very different than that for text, for example.

# AI CoE Architecture

With buy-in secured and a team in place, you can hone in on which problems the CoE will tackle first. The goal is to create scalable practices, but it doesn't make sense to try to apply AI to every single process in one fell swoop. To build scalable practices, start small. Identify and prioritize an ML opportunity that should be a relatively quick win, and build momentum from there.

In order to generate momentum, you'll need the architecture necessary to scale an AI practice. To manage this architecture successfully, organizations might turn to AIOps, DevOps' artificial intelligence-infused evolution. According to **Andrew Lerner of Gartner, AIOps'** platforms "utilize big data, modern machine learning and other advanced analytics technologies to directly and indirectly enhance IT operations (monitoring, automation and service desk) functions with proactive, personal and dynamic insight."

In effect, AIOps leverages AI to keep product and operations infrastructure running smoothly. If you're building scalable AI, why not continue to leverage its benefits for your incident management and other operations-related activities, like getting high-quality training data?




Source: Gartner

# Launch your Initiative by Building a Flywheel

## Scalable AI relies on strong training data practices, machine learning algorithm selection, and business analytics

Once you uncover the projects best suited for an AI-enabled makeover, you can prioritize which to look into first. This is where your project manager on the CoE team will come in. They will help you keep your AI initiative on task and remind everyone it's a marathon, despite the fact development cycles are referred to as "sprints".

The training data center of excellence is primarily responsible for acquiring and annotating the high-quality training data needed to build the algorithms for your project. Before you begin to sift through reams of information, your team must implement success metrics.

For example, organizations may want to determine metrics that measure the business impact they expect from AI, such as:

SAVING MONEY

GENERATING REVENUE

SAVING TIME

IMPROVING SPECIFIC EFFICIENCIES

These metrics will help guide the launch process. They will help you determine the types of data needed to build the algorithm and what kind of partners/vendors you need to engage with as part of the CoE workstreams.

If launching an initiative, it's likely that your organization already has become comfortable with a certain level of AI within its business processes. You've probably tinkered with AI for a smaller project and are now ready to elevate AI-enabled technology into production as a core part of your business.

To turn AI into a core part of your business, you'll need to build a flywheel—a mechanism that allows you to scale your training data-creation and model-building processes across other facets of your business.

# The AI CoE Flywheel

With a clear definition of success and your initial project underway, you can turn some of your attention toward building a self-fulfilling process. By now, the CoE team should feel empowered to go out and find other opportunities along the product roadmap. The ideal state for the CoE should be that AI becomes a core part of your company's products and services, not a series of one-off projects or experiments. Creating momentum for AI inside the organization is critical for elevating the AI function to a table-stakes member of the technology stack and product core feature list. Once you get the first use case permanently in production, the next ones will follow naturally alongside, leveraging that momentum. This process is like creating an AI flywheel within your organization. But what does success here look like, exactly?

It will create an engine that encourages people to come to you for AI-related projects. When you create a CoE that acts like a flywheel, you're creating a machine that is an integral part of the organization. You're moving out of the experimental group to core piece of driving revenue for the company.

Building a training data flywheel requires ingesting the appropriate data, annotating it, and developing an algorithm or a set of algorithms that address a business case. When developing an algorithm, you'll have a number of choices, each with its own set of pros and cons, depending on the size of your organization, the resources available for a CoE, and the purpose of the algorithm.

| | PROS | CONS |
|---|---|---|
| **PAYING**<br>for a vendor-produced model.<br><br>There is a growing market for ML model providers. AWS offers an extensive market with models for a variety of purposes. Google, Microsoft, and IBM Watson are just a few of the big-name enterprises that offer machine learning-as-a-service solutions for sale. | • The models provided by vendors are generally cheaper than building a model in house.<br><br>• The APIs that these vendors offer typically work with a number of use cases.<br><br>• Finally, purchasing a model typically allows an organization to get AI up and running faster. | • Despite the powerful APIs these models contain, they're very generic and offer limited, specific functionality. If your use case does not align well with what one of these models offers, then it will be of little help. |
| **BUILDING**<br>a model in house.<br><br>Working on a process that's core to your business? Then building a model your organization owns and can tweak when necessary is probably the best scenario. | • Building a proprietary model offers an organization control over the IP. This route will also yield a model that fits very specifically the use case in question.<br><br>• Finally, if more models are required in the future, building an initial test case in house can offer a strong foundation from which to work when developing subsequent models. | • Building a model in house is likely the most expensive—at least at the outset—option of the three.<br><br>• It requires an appropriate team in place, as well as the raw resources necessary to build from scratch, train, test, and maintain in production. |
| **OUTSOURCING**<br>model creation.<br><br>This is the option that perhaps best suits an organization that needs a more tailored model than what providers offer but doesn't have the resources to build one from scratch. You can partner with organizations like Provectus to tap into their existing AI expertise for model creation. | • Outsourcing a model allows for a more customized model without the initial overhead required of building a model from scratch.<br><br>• Outsourcing is a more flexible option than using pre-built algorithms and allows for more agile long-term planning. | • Paying a third party to create a model can end up being more expensive than anticipated if said party doesn't produce a model adequate for your purposes. |

Regardless of which approach to model building you select, you'll need the appropriate tools to guide you from data ingestion to model deployment. We offer a combination of a global crowd of annotators for creating high-quality training data and AI training data solutions designed to accelerate customers' artificial intelligence initiatives. While it's possible to build data-annotation tools in-house, it's often more efficient to think outside of the organization for certain parts of a CoE.

In the case of a CoE built for AI training data creation, it's likely you'll want to lean on successful and proven vendors to augment the infrastructure you've built. Focus internal energy and resources on developing cohesion among stakeholders and determining the vision and goals that the CoE will support. AI promises immense opportunity, and it's worth exploring existing tools to help leverage that potential.

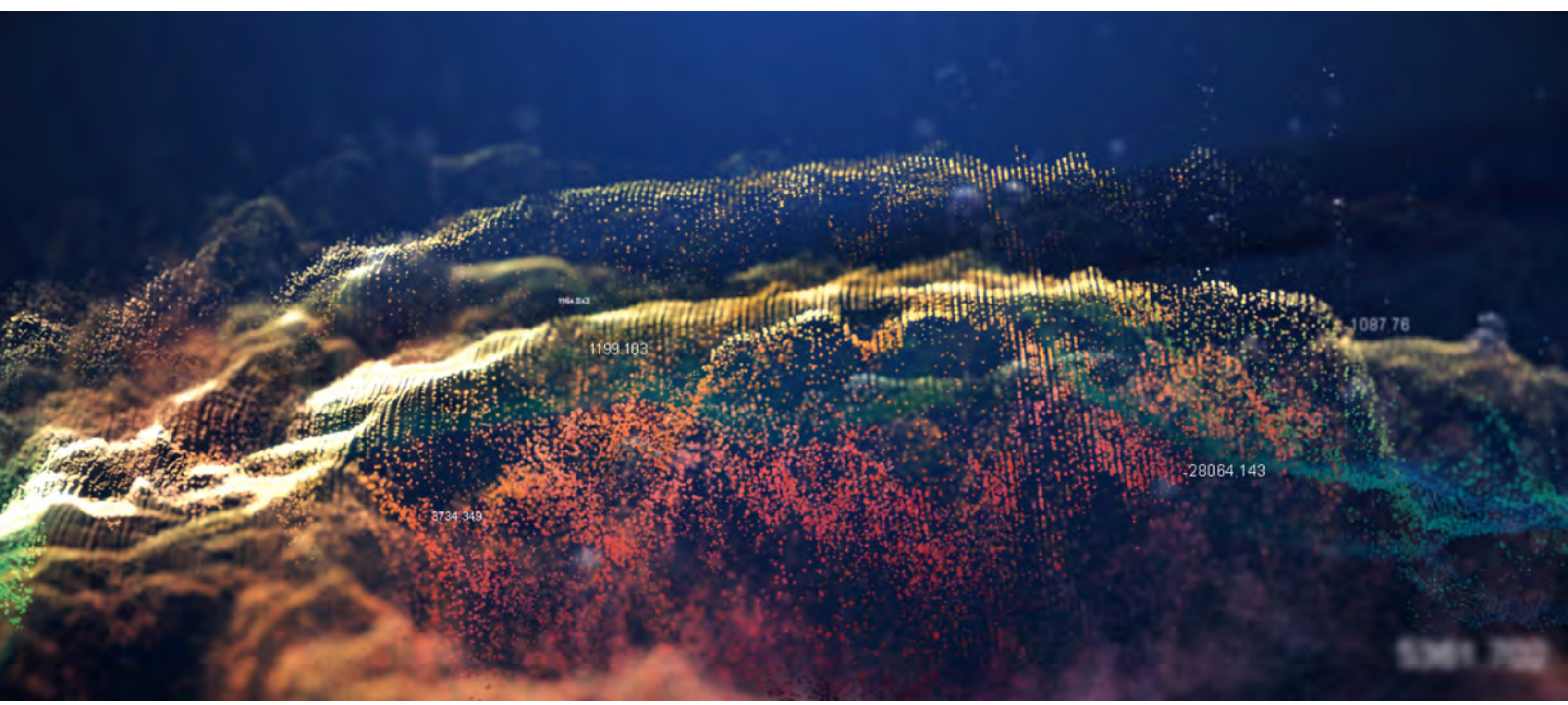
# Critical Success Factors for Enterprise AI

## Build Healthy Data Work Streams within AI Center of Excellence

Even after you understand the process necessary for building a center of excellence, you may find yourself asking, “How am I going to do this by myself?” Finding the right people and technology partners to make these processes more efficient and act as a guide along your journey will be invaluable.

It’s imperative you build a team with domain expertise and leverage solutions that enable you to annotate data at scale with high levels of accuracy and a large-enough crowd.

This type of tech stack, coupled with professional services to guide the entire CoE-creation journey, is uniquely positioned to deliver on the increasing volume, quality, and speed requirements for training data to support business innovations and efficiencies which use ML and AI.



# About Us

Appen collects and labels images, text, speech, audio, video, and other data used to build and continuously improve the world's most innovative artificial intelligence systems. Our expertise includes having a global crowd of over 1 million skilled contractors who speak over 180 languages, and the industry's most advanced AI-assisted data annotation platform. Our high-quality training data gives leaders in technology, automotive, financial services, retail, healthcare, and governments the confidence to deploy world-class AI products. Founded in 1996, Appen has customers and offices globally.

- **With 25 years of experience,** 15 of which in Automotive. We offer a full suite of multimodal computer vision annotation tools with in-cabin vehicle collection and NLP annotation services to help with your autonomous vehicle projects.
- **1M+ crowd in over 130 countries,** speaking 180 languages and dialects
- **Experienced team based in the heart of Motor City,** Detroit lends its expertise and resources on the ground to accelerate your product development and testing workflows
- **Data annotation expertise** ranges including conversational assistance, point cloud labeling (LiDAR, Radar), 2D labeling including semantic segmentation, and video object and event tracking.
- **Workflows:** Our simple user interface empowers teams to build and automate multi-step data annotation projects without relying heavily on technical resources. Break complex projects down into simple jobs, then automatically route data between the jobs using configurable routing rules. String multiple jobs or models together in a branching or linear configuration. Leverage machine learning in workflows to offset costs and expedite project completion.