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Smart operators: How leading companies use machine intelligence

Despite the recent and significant advances in machine intelligence, the full scale of the opportunity is just beginning to unfold. New research reveals why some companies are doing better than others.

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Making good use of data and analytics will not be done in any single bold move but through multiple coordinated actions. Despite the recent and significant advances in machine intelligence, the full scale of the opportunity is just beginning to unfold. But why are some companies doing better than others? How do companies identify where to get started based on their digital journeys?

In this episode of *McKinsey Talks Operations*, Bruce Lawler, managing director for the Massachusetts Institute of Technology's (MIT) Machine Intelligence for Manufacturing and Operations (MIMO) program, and Vijay D'Silva, senior partner emeritus at McKinsey, speak with McKinsey's Daphne Luchtenberg about how companies across industries and sizes can learn from leaders and integrate analytics and data to improve their operations. The following is an edited version of their conversation.

Daphne Luchtenberg: Earlier this year, McKinsey and MIT's Machine Intelligence for Manufacturing and Operations studied 100 companies and sectors from automotive to mining. To discuss this and more, I'm joined by the authors, Vijay D'Silva, senior partner emeritus at McKinsey, and Bruce Lawler, managing director for MIT's MIMO.

Let's start with the why. What was the main driver behind the partnership and why did we commission the research?

Vijay D'Silva: Over the past few years, we've had conversations with dozens and dozens of companies on the topic of automation and machine intelligence, and something came out of it. It was clear that we saw a rising level of attention paid to the topic. But at the same time, we saw many companies struggle while others succeeded. And it was really hard to tell why that was happening. We started by looking at the literature and saw a lot of what companies could do or a point of view of what they should be doing in this space, but we didn't really find a lot on what actually was working for the leaders and what wasn't working for the rest. So we launched this research to try and address the question.

What we really wanted to do was get a firsthand account across as many companies as we could find to drive both success and struggle across a fairly large weight of companies. Based on the interviews and the surveys, we can now map out the journeys that companies should take or could take in accelerating progress in this space. What was particularly important was it could define success and failure in many cases in some industries.

Daphne Luchtenberg: Bruce, a lot of people have had false starts, right? And we hear about bots and machine learning based on data analytics, but where did you and the team see practical examples where they were really starting to add value?

Bruce Lawler: We looked at over 100 companies in the study itself, and then we did deep-dive interviews with quite a few of them. And what we saw was that there really is a two- to threefold difference across every major operational indicator, and some examples of success stories came out. At Wayfair, for example, they use machine intelligence to optimize shipping, and they reduced their logistics cost by 7.5 percent, which in margin business is huge.

A predictive maintenance company called Augury worked with Colgate-Palmolive to use predictive maintenance, and they saved 192 million tubes of toothpaste. They worked with Frito-Lay and they saved a million pounds of product. Another example is Vistra, an energy generation company. They looked at their power plants and the overall efficiency, what they call the heat rate. They were able to reduce energy consumption by about 1 percent, which doesn't sound like a lot, but you realize they generate enough energy for 20 million households. Finally, Amgen uses visual inspection to look at filled syringes, and they were able to cut false rejects by 60 percent.

Daphne Luchtenberg: That's amazing, right? Even while philosophically execs have bought into the idea of machine learning, if we get down to brass tacks, there are real examples of where it's been helpful in the context of efficiency and in operations.

Bruce Lawler: There are quite a few different use cases where the leaders focus. Those are in forecasting, transportation, logistics and predictive maintenance, as I mentioned. But close behind those were quite a few others in terms of inventory optimization, or process improvement, some early warning systems, cycle time reduction, or supply chain optimization. The bottom 50 percent did not have this type of focus. So I think a key takeaway from the study is the laser focus of the leaders on winning use cases. And second, they took a multidimensional approach.

Historically, people thought if they hire a data scientist, that would be enough. But there actually were nine different areas that are required to be a leader, although you don't have to do them all at once. We'll give an example of Cooper Standard, which is doing a very cutting-edge, real-time process control using machine learning. To be successful, they needed three big things: strategy, people, and data. Strategy they had to, from an entire company perspective, decide that this was important to them, that what they had today wasn't good enough, but there were other solutions.

Second, they had to upskill the people that they already had, typically control engineers who did not understand data science and data scientists who didn't understand control engineering. They're almost exact opposite fields. Also, they gave people online access to data and they very much empowered their frontline people as well.

On the topic of data, they had too much of it. It's a very complex process that they have and they had to come up with new methods of data pipelining. They couldn't even use the cloud because the data was moving so quickly, they had to process it locally. And the process lines are running so quickly, they had to make local, real-time decisions.

Daphne Luchtenberg: Bruce, what other surprises did you and the team come across as you were completing the research?

Bruce Lawler: I think one of the main things was the efficacy and the efficiency of the leaders' ability to deploy at scale. For example, a buyer, an international pharmaceutical company, was able to use their governance process to triage the most valuable applications. They would then go to one plant where they were perfecting these applications. And once they've achieved the results that they'd hoped, they would rapidly deploy them around the world to their facilities. They ended up being classified as what we call an executer in our study, even though their performance results were that of a leader.

Vijay D'Silva: I had the same observation that Bruce had. And there were two things in particular that surprised me. One was we always expected the leaders to invest more heavily than the others, because they were far more advanced and were spending more money. What was surprising was that the rate of increase in the investments when we asked people to talk about future investments for the leaders was much higher than the rest. We were left with the feeling that not only was the gap large, but it was increasing.

The second thing that surprised me was the fact that the leaders don't have to be large firms and you didn't necessarily need the pockets to become a leader. We found plenty of examples of leaders that were smaller firms that were quite nimble but were able to pick their shots intelligently. That was one theme that came through across many of the companies that we saw, that the ability to focus their efforts on where it mattered made them leaders.

Daphne Luchtenberg: Thanks, Vijay. Just to press a little further there, companies across industries in a wide range of sizes from blue chip companies to greenfield sites, they're all trying to integrate analytics and data to improve their operations. However, the results have been mixed. Why do some companies do so much better than others?

Vijay D'Silva: It's an interesting question, Daphne. We looked at nine different things—nine different levers that companies could pull. And out of nine, five really stood out at us that really make the difference, and they were the following: governance, deployment, partnering, people, and data. Governance means to what degree is there a top-down push from senior management, and also a purpose-driven approach to deploy the technology. Leading companies have strong governance to keep the digital programs on track and to document how the portfolio is doing. For example, a pharmaceutical company put a lot of effort to use AI in some of its plants across a number of use cases, and then had work to that applied across the network. Leading firms will actually do this quite rigorously and regularly.

The second thing is, especially given the dearth of talent in data science in the industry, leading firms are much more purposeful in terms of how they organized. The poor performers were more likely to spread their resources thin across multiple teams or not have them at all. In contrast, leading companies like McDonald's, as Bruce mentioned earlier, would be more likely to have a center of excellence where they would concentrate their resources.

Deployment is literally to what degree our use cases were used and in what order. Leading companies had much more of it and were much more conscious of which ones mattered. And then as we took it into partnerships, partners were far more common across leading firms than the rest, which surprised us initially. But they were more reliant on either academia, start-ups, or existing technology vendors or consultants, and use a wider range of partners than the rest. An example, was the company Augury that Bruce mentioned before, used by both Colgate-Palmolive and PepsiCo Frito-Lay, and essentially, using AI-driven systems and what's available out there in the market to generate impact. Analog Devices is a semiconductor firm that collaborated with MIT to use machine intelligence quality control to use production runs or defaults in production runs.

The last one is data, specifically the democratization of data, where leaders normally put much more effort into making sure that data was accurate. Ninety-two percent had processes to make sure that the data was available and accurate. But also the fact that it was available to the front line. In contrast, over 50 percent of the leaders had data available to the front line versus only 4 percent of the rest.

Daphne Luchtenberg: Thanks, Vijay. And Bruce, we've talked a bit about the four categories that the research settled on. Can you talk through what those four categories are and how you define them?

Bruce Lawler: The leaders really captured the largest gains and had the largest deployments. As a result, they have the most infrastructure and the most capabilities across the company.

Then there was the middle ground, what we call the planners in the executer, which have really good maturity on the enablers, they've invested in people, data infrastructure, data scientists, and their governance processes, but they haven't yet proceeded far enough along their journey to get the same results as the leaders.

Finally, we come to the executers. Executors were hyper-focused on very simply getting solid gains and typically broadly deployed as the buyer example I gave earlier. To give you an idea of the differences, if I compare the leading to the emerging, for example, leaders had about 9 percent average KPI improvement versus the emerging companies at 2 percent. Leaders had a payback period of a little over a year, where emerging companies were at two years. So, double. In terms of deployment, leaders were doing 18 different use cases where the emerging companies were six on average.

Daphne Luchtenberg: How can companies get started on their digital journey? What do they do first?

Vijay D'Silva: We found a lot of bad companies that should've not started. If there was one thing that we really learned from talking to the leaders, it's to start with what matters to you. There was plenty of evidence of companies starting on certain use cases and others trying to replicate that experience, which tended to fail unless it was a problem that really mattered to them. The context of each company and their strategy, we realized, was extremely important. The first thing was to start with a use case that really matters.

The second thing is around making sure that the data is available. And we've talked to the course of this effort in this podcast about how data is important. Leaders take data extremely seriously, very often baking it into the early parts of their

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processes. It’s making sure that the accuracy of the data is right and the availability of data is right. This has changed from a few years ago. Finding a vendor with a proven solution is often one of the fastest things that companies could do. There isn’t a need to reinvent the wheel, and the vendor landscape has simply exploded over the past few years and there’s plenty of help out there.

The fourth is driving to an early win. Momentum is extremely important here, and leaders realize the value of having a strong momentum here to keep the engine running. Therefore, we’re starting with an early win to build up the momentum to gradually become more sophisticated over time.

Daphne Luchtenberg: Thanks, Vijay. And Bruce, we talked earlier about the importance of kind of engaging with a broader ecosystem. And that from that comes increased momentum. What did you see the leaders do in this area that was really interesting?

Bruce Lawler: This was another surprising finding. The leaders actually do work a lot with partners, even though they’ve spent excessively on their internal infrastructure; that’s to help them pick the best partners. Some of these partners are risky, with longer timelines. For example, leaders tend to partner with start-ups, which is typically a little riskier, or they partner with academia, which leads to longer timelines. I’ll give you an example. Analog Devices worked with MIT on one of their ion implantations processes. That’s part of the semiconductor manufacturing process and it was important to them to really get this right, because the way semiconductors are made, you lay down one layer and it could be months before you finish the entire chip and you can test it. In this case, it was worth taking the risk to determine if a process months earlier actually ruined a product that you then spend more time and money on.

Daphne Luchtenberg: I suppose it’s a little bit counterintuitive, as we’ve been talking about bots and machine learning, that Vijay, both you and Bruce have talked about the importance of the people component. Why is that? Does it turn out to be such an important indicator?

Vijay D’Silva: I cannot overemphasize how important this one factor turned out to be. I know it sounds trite, but as we dug in through what different companies are doing, it was eye opening in terms of what was happening on the people front in two key ways. One is in terms of building skills, and we talked about centers of excellence, to what degree leaders of building skills due to power and some of these efforts. The leaders had thought about roles that the others hadn’t even gotten to. For instance, things like machine-learning engineers versus simply data scientists and data engineers. And there were four or five different categories of people that the leaders were building into the process, thinking three or four steps ahead.

The second thing is that there was greater emphasis on training their frontline employees. We saw this. We mentioned McDonald's before, where even though there was a core within the company that was developing applications for forecasting footfall, for instance, there was a greater degree of emphasis on training the frontline staff to be able to get the most out of it. That was a theme that we saw across multiple companies.

And then the third one is around access to data. The leaders were much more willing to give access to data to the front line and across the board, across the company in a particular firm, versus the rest of the companies that will sometimes tend to be much more guarded around how they use data. That was the third thing in terms of providing frontline employees and employees in general with the resources and the data that they needed to succeed.

Daphne Luchtenberg: Bruce, a lot of our audience who follow *McKinsey Talks Operations* will be thinking about their own careers, their own personal development plans. How should they be thinking about building their own skills in this realm?

Bruce Lawler: This industry is moving so quickly, and you cannot keep up with it. It's really a large and complex field, so no one person can know everything. What we found to be successful was a team approach. So I think, learning who your trusted partners can be, whether the vendors or even sometimes your customers, start-ups, academia, or your new employees, that's going to be what's important. And you really need to get outside points of view. Even if you're a digital native, it's a diverse space.

Daphne Luchtenberg: Thanks, Bruce. That's great. Vijay, we're coming to the end of our program, and we must thank you, Bruce, and the team for pulling this really interesting research piece together and giving us kind of a road map. Can you just give us a sense, regardless of what category an organization might feel they're in—a leader, a planner, an executor, or an emerging company—how should they be moving ahead? How should they be focusing on the next step?

Vijay D'Silva: There were four things we identified in the work that we did. The first one was having some sense of a North Star. There was always the risk that companies would bounce from one pilot to another pilot to a third. To the question, having a clear-eyed view of what the end game is—the North Star, the goal, or whatever you call it. It was extremely important, because that would guide a lot of future effort. The second thing we were struck by, across many companies we talked to, was there wasn't enough clarity about where they stood versus their peers. The thing we felt was fairly important was to just take an honest self-assessment in terms of where they stood compared with state of the art today or state of practice.

The third one was having some sense of what a transition plan would be. So for instance, there are many paths to becoming a leader, whether you go and execute first, or a planner, and having some sense of how to get there was important. Now we recognize that the industry is changing so fast that

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—Bruce Lawler

the plan might change, but it was important to have a point of view, so that companies wouldn't spread their investment dollars too thinly. The last one was the importance of having use cases—a handful of use cases that matter to them. And starting with those and building up momentum from that. Having a clear sense of what those use cases are and making sure that the momentum and impact from that was important.

Daphne Luchtenberg: Brilliant. Thanks, Vijay. And Bruce, we pride ourselves on this *McKinsey Talks Operations* series that we always get pragmatic and it's not theoretical, but it's about what can we do next. So if I were to ask you, what's the one thing that our listeners should know, should read, and should learn, how would you guide them?

Bruce Lawler: What they should know is the types of problems that make good machine-learning problems. For example, if it's a very high-volume problem with a large number of transactions or large number of products or if it's a high rate—short cycle times or short decision times—or it's high complexity, where there's many interactions of different systems coming together, or it's a highly sensitive process that requires very tight controls—as far as what you should read, any article that really describes how others have successfully used machine learning, that will give you ideas on what problems to solve. So, focus on the what, not the how. You want to be successful quickly, so learn from other examples. And as Vijay said, pick ones that are important to you, and then duplicate the methodology.

Last, what you should learn is, what type of problem are you trying to solve and what types of problems are solvable by machine learning? So for example, is it a classification problem? Am I trying to classify dogs or cats? Is that a clustering problem or am I trying to take groups of things and group them together very much like we did in this study? Prediction—am I trying to predict if something will fail in the field in the future, even if it's working just fine now? Or an anomaly detection, which is something really different than something else.

Daphne Luchtenberg: Bruce, can you say a bit more about the companies that participated?

Bruce Lawler: A little over half had 10,000 or more employees, so they are a little bit on the larger size. But 45 percent, actually, were under 10,000. And to break that down a little bit, 12 of them had just 50 to 199 employees, so they were quite small. And as far as range of industries, we covered everything from oil and gas to retail to healthcare and pharma, aerospace, automotive. So, 17 total categories of industry.

Daphne Luchtenberg: And Vijay, now that this research chapter has come to an end, what are the next steps? And what can our listeners look out for?

Vijay D'Silva: We published this on both McKinsey and MIT websites, and we're very excited about that. We love your comments and there's been a fair bit of debate that this has generated, which has been fantastic. And then in parallel what we're doing is going back to each of the companies that participated with our results, which includes where they stand versus the others and what that might mean for them. It's a different story for each one, which is going on as we speak. As this proceeds, our hope is that over time, we expand this to a greater and greater share of the industry, but both in terms of manufacturing and operations more broadly.

As Bruce mentioned before, we've got 17 industries covered in this study. And over time we'd expect that to deepen as we get more and more companies, each of the industries, suspecting that the story, the implication would be quite different by industry and by company depending on the size they are, the maturity that they're in, and where they hope to get to.

Bruce Lawler: If I could just add that we are creating these individual playbooks for each of the companies so they can see exactly where they are on their journey and what are the immediate next steps that they should be doing on their path toward being a leader or certainly getting better KPI performance and faster paybacks.

Daphne Luchtenberg: Bruce, thank you so much for sharing these insights. Vijay, thank you very much for being part of this conversation. I summarize it as some of these efficiency gains and operational gains are definitely within reach, and those companies that haven't yet made the first move, they should do so forthwith. Would you agree, Vijay, Bruce?

Bruce Lawler: Absolutely.

Vijay D'Silva: Absolutely.

Daphne Luchtenberg: Thank you so much for spending some time with us today. And we look forward to being back with you all soon for our next program of *McKinsey Talks Operations*.

You've been listening to *McKinsey Talks Operations* with me, Daphne Luchtenberg. If you like what you've heard, subscribe to our show on Apple Podcasts, Spotify, or wherever you listen. We'll be back with a new episode in a couple of weeks.

Bruce Lawler is managing director of the Massachusetts Institute of Technology's Machine Intelligence for Manufacturing and Operations program. **Vijay D'Silva** is a senior partner emeritus in McKinsey's New York office, and **Daphne Luchtenberg** is a director of reach and relevance in the London office.

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