Center for Digital Strategies
Tuck at Dartmouth

Decision-Making: Data and AI

A Roundtable Overview
Americas Chapter Discussion

Roundtable on Digital Strategies

Decision-Making: Data and AI

Thought Leadership Roundtable on Digital Strategies
An executive roundtable series of the
Center for Digital Strategies at the Tuck School of Business

Since the Roundtable on Digital Strategies first discussed big data in 2012, the data explosion has only accelerated. At the same time that enterprises are looking to use data in new and different ways to create value and unlock their full potential, the threat of start-ups exploiting the very same data to disrupt established companies is increasing. Artificial intelligence has become the top new technology investment to help evolve beyond data collection and make better and faster data-driven decisions — with profound implications for corporations' strategies, operations, and culture.

The Americas chapter of the Roundtable gathered in June 2018 at Airlines Reporting Corporation in Alexandria, Virginia to discuss the business and organizational impacts and consequences of the evolution from 2012's 'big data' to the growing emphasis on data science supported by artificial intelligence and machine learning. Participants included CIOs and chief data scientists from host Airlines Reporting Corporation (ARC), Chevron, Eastman Chemical, Evolent Health, Sysco, Tenaris, and Tetra Pak, as well as the Directors of the Center for Digital Strategies of the Tuck School of Business at Dartmouth College and its Executive Fellows.

Key Insights Discussed in this Article:

- **Focus on the customer is more important than ever.** As digital-native start-ups threaten established companies from unexpected directions, the best defense is to use scale and privileged insights to deliver value through new and differentiated data-enabled offerings. …………………………………………………………………...…….. **Pages 1-2, 8, 10, 12**
- **Technology is first and always in support of the business.** Companies need to avoid being swept up in the hype around AI and machine learning, and instead focus on how these tools can enable scalable and repeatable processes in support of faster and better decision-making. ………………………………………………………….…………….. **Pages 2, 5, 7, 11**
- **Data governance is critical as both carrot and stick.** As customers and regulators become more sophisticated and more strict, enterprises need to be even more rigorous about privacy and trust. At the same time, data governance with transparency and accountability opens up whole new domains of potential opportunity. ....……… **Pages 1, 3, 6-9**
- **The pace of technological change is creating existential problems.** After nearly 50 years of Moore's Law, both people and companies may have reached limits for how quickly they can absorb technology. Not all will make the transition to a world where AI is commonplace. ………………………………………………………………………………. **Pages 5, 8, 10-12**

This overview was written by Stephen Plume, Executive Fellow. The Roundtable on Digital Strategies publication series is edited by Hans Brechbühl, Executive Director, Center for Digital Strategies (www.tuck.dartmouth.edu/digitalstrategies).

What Has Big Data Done for You Lately?

"There has been so much change in just the two years since we last talked about this topic," began Hans Brechbühl, the Executive Director of the Center for Digital Strategies. "Technology is changing a lot, especially AI; skills that people need are changing. Data is at the heart of it: How we bring data to bear in order to make better and faster business decisions. So where are we, and where are we going?"

"We are the furthest along in supply chain," volunteered Mike Paulonis, Head of Data Science at Eastman Chemical. "The data is readily available, the problems are very tractable. I could name a dozen different optimization applications. We've gotten a lot of mileage out of analytics in that space. Plenty of others as well, but not as far towards their potential."

"We also see a lot of opportunities in supply chain," agreed Roy Krzywosinski, VP of Engineering at Chevron. "Another example is manufacturing: In years past, you might be optimizing the system, but sub-optimizing the plant. Analytics now identify which systems to sub-optimize in order to optimize the whole plant. Asset integrity also comes to mind: We can use predictive analytics to understand how long that vessel, this tank, that pipeline will last."

"We've had some narrow success in anticipating customer needs," added Keith Sturgill, CIO of Eastman Chemical. "We developed models to anticipate when customers would need to top off heat transfer fluids, and the sales channel proactively made those calls at the right time. We had a significant increase in business, and I'd like to see us do more of it."

"We have a similar example in our downstream lubricants business," Jim Green, Chevron's GM of IT Service Delivery confirmed. "It started as CRM technology for our channel partners who wouldn't make that kind of investment. Our goal was to get them a better demand forecast. Once they started using it, we could run analytics on their most probable customers and start to recommend top-offs. And then we started to squirrel away market share, which we really hadn't seen coming."

Wayne Shurts, CIO at Sysco, continued with the theme of anticipating customer needs:

> In category management, we deal with hundreds of thousands of products: What to buy, who to sell them to, pricing. Our merchandising group analyzed all this to create opportunities for our sales force. And we created so many opportunities, it flooded them. Sales couldn't do anything with it. So that was the 'big data' thing. So now we're starting to use AI to identify which are the hottest opportunities, and that's actually starting to make a difference.

"In the whole phase of big data, companies created centers of excellence around analytics and data science, and they operationalized based on those technologies," explained Dion Hinchcliffe, Chief Strategy Officer of 7Summits and Executive Fellow of the Center for Digital Strategies.

> And they soon recognized two problems: One, that many companies can't get access to all the data that they need for advanced analytics, because there's still a significant data

silo problem. The real challenge is that analytics tools are giving more insights than we can operationalize: Fewer than 5 percent of insights are ever acted upon. Analytics swamp the business with information that can't be effectively used, and it just piles up, while even more flows in. So there's a lot of interest in getting help to take action at scale.

> That's where AI makes analytics more real, more tangible, and delivers results to the business: It helps to identify the things you don't have time to look at, to make the decisions, and to take action at scale. That's the operational piece that AI delivers, rather than just putting up a lot of dashboards and reports. So now the focus is, "How do I help the customer?" Everyone is going where the bucket of revenue is, and that's the customer experience.

"There's definitely been value in leveraging data," summarized Navin Advani, Sysco's VP of Supply Chain & Merchandising Technology and Enterprise Data & Analytics Platforms.

> In cost reduction, in supply chain and merchandising, in customer experience and category management. The next challenge, though, is how to start to leverage AI and machine learning. How can we realize the descriptive and predictive capabilities of AI and ML versus advanced analytics, and use that delta to make better decisions? How do we start to automate, and disintermediate some of the horde of business analysts we have looking at the data?

Flipping the Script

"We've got to remember that AI, machine learning, deep learning — they're all means to an end," Sturgill reminded everyone.

> The goals of our business haven't changed: In the manufacturing world, it's still about operating our plants safely, reliably, and with the right level of quality. That hasn't changed — but the tools that we have to help us do it better are transforming. We try to begin with the decision we're trying to make. Not the process, not the technology: What's the decision?

> And then we apply these techniques to enhancing the speed and quality of those decisions. How do we leverage the technologies — and the techniques, even more than the technology — to really differentiate our business in the marketplace? AI is something you *do*, not something you buy: It doesn't supplant deep knowledge of your business.

"From a start-up's perspective, it's true that our customers are just trying to answer business questions," stated Steve Plume, VP of Marketing at conDati and an Executive Fellow of the Center for Digital Strategies. "We happen to use machine learning, but they don't care if it's machine learning or AI or data science or what. They care how quickly they can see business insights that they can act on."

"We don't think about data first, we think about what the customer needs," agreed Ksenia Kapoor, Senior Director of Program Management at Evolent Health and a Tuck alumna. "*Then* we go back and look for insights in the millions and millions of records that we have, as opposed to saying, 'We have this data, let's get the great insights out … Now what do we do with them?' It's flipping the script."

"Any use case has to answer the 'So What?'" Advani asserted. "While you're capturing the data, what's the outcome that you want to get from it? There are two methodologies: You can capture all the data and then figure out how to use it, or you can have an end goal in mind, and then go figure out the data that you need."

Eduardo Galindez, Senior Director of Industrial IT & Digital Solutions for Tenaris, supported Advani's idea:

> We work in two ways: Data generation, and in finding new technologies to generate information for manufacturing and logistics. We leverage data analytics for safety, and image recognition. That data goes into the efficiency of our operations, without any need to generate new data.
>
> There is also an opportunity to generate new data using disruptive technologies: An opportunity not just to do things better, but to do things that we don't do today. If we only try to solve problems that we know, we are not using data in a creative way.

"I can't imagine a situation where you just have people diving into the data and trying to find 'something,'" Paulonis objected. "That's not business. Maybe it happens, but I think most people tend to approach things business-first."

"Then how do you ensure that the data scientists get the right challenge?" asked Noah Schellenberg, Lead Data Scientist at Tetra Pak. "They come to a company and they want to do machine learning and AI, and then all of a sudden they're being asked to just make some stats about the data. Maybe that's helpful for the business, but .…it's not well understood that there's a difference in skillsets between a data scientist and a business analyst."

"We have people who go from descriptive to prescriptive analytics in the same organization," Paulonis answered. "If the business needs descriptive analysis of the data, we can deliver value. If we find a need for a prescriptive model, we can give that to people who do optimization."

"We've tried to blur the boundaries between our data science group and our front-line business people," Paulonis' colleague Sturgill continued. "We haven't followed the traditional IT models around defining projects and values and problems. We purposefully don't put heavy governance around it: We want those people applying their knowledge and their creativity to solve whatever the business is struggling with. If they happen to use AI to do that, great; but it's not about AI, it's not about governance, it's about business performance."

“We also need to keep in mind that even though we have heaps of data, the data by itself intrinsically has no value unless you can actually turn it into value adding information,” Krzywosinski pointed out.

> We want to be decision-driven — meaning, have the right information to make a high-quality decision. What data do we need for a high confidence level? Because I don’t want any *more* data: I only want the data I need to make a high-quality decision. So one of the challenges we have in this world of huge data sets is having the skillset — or the genius — to pull out the data, and only the data, that we need to make that high-quality decision. Many times we just drown in data, and we create a lot of swirl looking for that next piece of information that might tilt us one way or another — when in fact the value of that incremental piece of information is zero.

“There is a combination between the two approaches,” Galindez suggested.

> When you’re in the data, you’re limited only by your imagination. You are not finding the correlations that you want? The machine is helping you. So there’s an evolution — but the business is always important, because they will be the ones to validate if your correlations make sense or not. In some cases, we don’t know where we’re going to wind up, but if we approach things top-down and bottom-up, there can be value in both.

“In a different way, aren’t you still trying to solve a problem?” asked Mark Meyer, Head of Global Information Management for Tetra Pak.

> The problem might be to increase efficiency, or to reduce effort. And maybe you don’t know how to go about that, so you have a broader attack. But you still have a traditional business problem and you’re solving it.
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> Then there’s also the question of how to do something better than before? Now that I have information, I actually have something someone else wants, so I can monetize it. We collect information on all our customers — we know more about their operations than they do, and we can build that into an expert service scenario. This is early, and there are lots of tools and capabilities, and I have a hunger to figure out what I can do with them.
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> Some of that’s okay, because until we start to get in there, we don’t know what it is, and if we over-govern, we’ll squash learning and cultural change around inquiry. So somehow there must be a balance, and a certain level of freedom to go out there and fail.

Chuck Thackston, Managing Director of Data Science and Research for ARC, gave an example of the inquiry-based approach:

> We saw a shift in a particular travel purchase behavior, and we were able to uncover some consumer behavior that led to our agencies looking at different ways to service customers. What we learned was that we need to take a broader look at *all* the data. Stuff is going on — why? We have a lot of different data points we can look at.

> The challenge we run into is that we can spend a couple of weeks on a model that may or may not be insightful. So now we're stepping back and asking how we can be more efficient at applying a tool that creates a lot of different models, and identifying which are the most interesting, and then our analysts can drill into those.

"The way data is now organized and the way you can mash it opens up possibilities to weld perspectives together that we didn't have before," Green agreed. "That gives the business a lot of flexibility. The risk is in making that process repeatable and keeping it fresh."

Handle with Care

"The biggest challenge we have is the repeatability," Schellenberg confirmed.

> "Model management" is creating a metadata system of all the models your data scientists are publishing, whether they're for experimentation or already chosen by the business. We don't see one solution that fits all. When you can get the business to forget about if whether something is deep learning or not, when you can get them just to give feedback on the model: that's when everything can start to be de-mystified, that's when you can start to offer data-science-as-a-service.

"We struggle with repeatability, too," Advani agreed. "Our field sales force is closest to our customers, and they learn about our competitors, about what other products our customers are buying. But we don't have a good mechanism to ingest this information so that we have the right data that will train, and then retrain the models."

Doug Mangold, VP Product for ARC, offered an example:

> One competitor gets some differentiation, then others catch up, and there's another hunt for a new data source that can somehow give an edge — as short-term as it may be, because what you have is an airline seat. There's a lot of talk about personalization, but making personalization work hasn't caught up to the data. Finding the tools to bring in those new sources of data and relate them has been a struggle.

"This brings up the question of who understands the data well enough to know the implications," observed Patrick Wheeler, Assistant Director of the Center for Digital Strategies.

> There's an example of Starbucks in New York, when they introduced pumpkin spice latte a week early to try to fix early fall sales numbers. It did shift revenue forward a bit, but with how far out they had to schedule in New York, they couldn't ramp staff to cover the volume.
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> They made a decision that was data-driven, and actually wound up losing money. Who's making the decisions, and do they understand the data really well, is a big challenge for organizations. This is the storytelling part of data that's so important.

"Those are the stories you're going to learn from because you never saw them before," Meyer proposed:

> One of our customers wanted unique QR codes on every package in order to run a marketing promotion. When people started scanning the codes, our customer learned that their product was being consumed in places they had no idea of as it was sold, and then sold again. They learned they had markets in places they didn't know there was a market, just from watching how the package moved from one place to another. It was one of those implications they weren't quite ready for, but it meant they could change their whole distribution strategy.

"In all these examples, everything seems great," observed Alva Taylor, Faculty Director of the Center for Digital Strategies. "Can you envision using data, using artificial intelligence, to actually hurt the customer experience, or hurt the value you create? Or is it all upside?"

"There's a creepiness factor that can occur when you look at personalization," Hinchcliffe answered. "If you show too fast how much you know about the customer, it freaks people out. It's like going on a first date: Everyone's done the research in advance, but you want to avoid the appearance of knowing too much."

"We've all experienced bad bots," Schellenberg agreed. "You think something will lower your cost, but from the customer perspective, it performs horribly and creates a negative experience. That's bad AI."

"You do have to be careful with using all this data," warned Dickie Oliver, ARC's CIO.

> It's not the risk of using the data incorrectly, it's the risk of consequences that don't solve business problems or satisfy customers. An airline person was talking about the importance of plane turns at gates, and going through the analytics of when the plane hits the ground, how long it takes to taxi, when maintenance arrives to clean — they were so excited about this whole metric process they had put together.
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> So I asked the question, "How do you know that the person who was supposed to get on the plane actually got on the plane? Isn't that the purpose of what you're trying to do? You know he's on the ground and in the airport, and how many times does he walk up to the gate and find it shut because you wanted to turn your plane more quickly?" The maniacal focus on data can lead to unintended consequences that cloud the real purpose.

"Balancing is a key aspect," said his colleague Thackston, adding another example. "We spend a lot of time calibrating our fraud identification models, because we want to avoid false positives. But there's also huge upside to finding fraud as we see things coming through the data. So the model always has to test: Is detecting this particular instance a good thing, or a bad thing?"

"There is a concept in machine learning called 'overfit,'" Galindez explained. "You train the model so much that it starts to behave in unnatural ways. You can't build a model and live with it: It's something that you constantly maintain, and pay attention to the false negatives and the false positives. You're fielding a lot of information, and you have to be very careful, because at some point the model will start to behave in ways that you don't want."

"It gets back to the whole business case, and to tools to make better business decisions," Taylor mused. "I was talking with a financial institution using machine learning to help with anti-money laundering. The model got so good, it was identifying too much, instead of just the big cases. It was costing them more to review the cases than they were losing in fraud — it was actually *hurting* their bottom line. So thinking about the business purpose is really important in setting the parameters for these models."

"Now Everyone Wants the Data"

Brechbuhl asked about another dimension of responsible use of data: "What's the decision matrix about when it is okay to share customer data outside the enterprise?"

"We have a data distribution policy that is approved by our Board of Directors," ARC's Mangold answered.

> It governs how our data can be distributed to the public and to our B2B customers. It talks about what level of aggregation we need to have, and how much volume there needs to be in any particular market before we can share it. Each of our products needs to conform to the policy. It protects our customers' proprietary information from their competitors, so it gives a general sense of where the market is, but not actual fare data.

"The challenge is that our airline customers change their perspectives on what is confidential and what is not confidential due to GDPR and other things, there may be changes to the data that have downstream impact," Thackston added. "So we have to be continually vigilant, because protection of the confidentiality of the data is absolutely essential."

"You're describing a traditional and sensible accountability at the time of data collection," commented Omer Trajman, Founder of AskFora and an Executive Fellow of the Center for Digital Strategies.

> In fact, for data at ARC, there's an accountability check before the data is released, and only data that meets that standard is released. This was natural when data was hard to capture, but now it's getting easier and easier. Does it limit opportunities?
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> Another approach is to apply governance to every single bit of data you collect: Where did it come from? What are my responsibilities around it? If the data comes with this kind of governance and lineage, could you let people experiment, but hold them accountable at the other end?
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> This kind of accountability requires transparency, and we are much less comfortable with this degree of transparency in the US than they are in Europe. But if I'm willing to report back to you my usage of the data, can we identify opportunities that are currently missed?

> We almost have to flip our thinking around, and apply governance and accountability to everything we do.

"One issue with that approach is that we have to do the right thing for our complete body of customers," Thackston replied. "There are also regulatory hurdles and multijurisdictional issues, where things might be okay with some, but not with others in a particular domain or jurisdiction."

Shurts described the data privacy discussion so far at Sysco:

> The European view of data is that an individual or a company lends you their data to do something with it, and you can always get it back. In the US we may not have quite that view: We tend to believe that it's our data. But the GDPR view is going to become more global, and regulation is going to follow along those lines. So we're talking about what we have to put in place for GDPR, and how to get ahead of what regulations we think are coming.

"We made the decision right up front that we were going to apply GDPR globally, period," Sturgill declared. "If you meet the GDPR standard, you meet the standard for the rest of the world, and the states within the United States. We'll see whether that turns out to be true or not."

"These topics of privacy and trust and security are going to be the most important issues with customers going forward," Hinchcliffe asserted.

> Cambridge Analytica was just the beginning. We need to take a lot more care to secure the data and inform our customers and cut them in on whatever money we're making off them without their knowledge. We've got to take this very seriously, or it's going to be taken out of our hands. GDPR was the first big shoe to drop: Because industry didn't take the leadership, they're now forced to deal with these ridiculous regulations that don't seem possible to comply with right now.
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> There are great things we can do with the data, but the consumer market is wising up to the fact that they really own their data, and that we should almost pay them for it, and it's going to be the same with B2B data. It's going to boil down to, "Don't do anything with your customers' data without their permission and without their knowledge." And it's the last piece that's going to be hard.
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> For practical purposes, customers have no problem with sharing their data with suppliers and business partners. Those agreements are shrouded by compliance. It's all the other unexpected ways that information can leak out of our systems or be mis-used.

"Data leak prevention is tough," Galindez agreed. "In the end, data is managed by people, no matter what GDPR says we need to do to protect the information. The classification and encryption of information, regulating the access, and trying to close the doors to leakage as much as possible, is going to be vital."

“Historically, data was contained within the IT group,” Oliver explained. “They used most of the data, they owned it, they understood it. Now everyone wants the data, and we haven’t collectively cared for it and tended to it. So when we start to propagate it out to a larger audience, the business starts to feel the real world pain.”

“And That’s When the Problems Start”

“Appropriate classification is critical,” Sturgill emphasized.

> We’ve had classification in place for years, but to say that it’s consistently applied is naïve. We would love to think that we know where all the data is, and sometimes we can fool ourselves into thinking that we do. Then we go to a meeting, and we learn we know maybe 50 percent of it. But as we start down the path of technology enabling us to leverage classification, to physically limit what you can do with the data — that’s going to be game-changing.
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> Enforcing data classification gives you the ability to make it more accessible to the broad masses, which leads to more insights and better business. You secure what really needs to be secured, and then you open everything else up. It’s going to be a big, big change, but being able to enforce policy is a necessary step towards pervasive access to data that doesn’t really need to be secured.

“The principle of least-privileged access forces teams who need data to fill out 6 forms and get 18 approvals,” Thackston laughed. “By clamping it down so much, we almost encourage leakage. We need to get better at saying ‘*This* data really needs to be protected,’ and make the rest of it readily available: ‘If you need access, you don’t have to tell me why. I appreciate your judgment, and protect it appropriately.’ It will eliminate the incentive to do bad things with the data.”

“At the end of the day, people are going to get their jobs done,” Trajman observed. “They’re either going to bring you along, or they’re going to work completely around you. And that’s when the problems start.”

“It’s about being able to instill a sense of shared ownership,” Hinchcliffe suggested.

> When you own something, you take care of it, you worry about it because it’s valuable. So governance has to be an inclusive process that makes people understand from the beginning that the data needs to be in service of the key stakeholders. This is our challenge: Governance has as much to do with people as with technologies. We have to free the data from the siloes, and get everyone into the shared-service mentality that says, “This data belongs to the company, and must be put in service to the customer.” That’s the hardest part.

Brechbühl followed up on the people part of Hinchcliffe's statement: "A recent survey[1] shows that virtually all firms — 99 percent — are trying to move to a data-driven culture, but only one-third are succeeding. This gap shows up in the survey every year, and it hasn't improved over time. Clearly firms need more concerted programs to achieve data-related cultural change. Many start-ups have data-driven cultures from the beginning, which is one reason established firms fear disruption from the newcomers so much. Why aren't firms making progress?"

"When I started at Sysco, we had tons of data going to our field," Advani answered.

> Over 100,000 reports went to people's inboxes. It was information overload, without insights: all rows and columns of data, with nothing actionable. It was a cultural thing to need all that information, but there was no standardization: We relied on tribal knowledge, and I'm not sure there was any true value coming out of all that reporting. Trying to shift to an exception-based culture, to look at the data that matters instead of at everything — it was difficult to wean them off that methodology.

"One issue there might be simply inertia," Brechbühl suggested, "But is it possible that they didn't trust the insights of the more abbreviated format? They had to see the source for themselves, and draw their own conclusions, to be comfortable?"

"It's a little of both," Advani acknowledged. "'I need to have what I've had the last 30 years,' that's the inertia point. And, 'Do I really trust the insight that a machine is telling me, rather than the 30 years' experience I have in the field?' That's the cultural problem. And that's the biggest challenge to success: Getting the organization to adopt and trust the data and insights from this new methodology."

Can We Get There Fast Enough?

"And the maturation of AI has created a whole different problem of fear, uncertainty, and doubt," Sturgill added.

> "If the machine is going to start doing what I've been doing for 30 years, what am I going to do?" That creates all kinds of behaviors that are not directly linked to AI, but it's human nature. The fear of "What am I going to do now?;" the uncertainty around "Can I can trust this model?;" the doubt over "What happens to me? I'm still accountable for results: Can I trust it?"

"It's still early days, but we try to explain to people the general workflows, then break those workflows down and show which parts will be automated and where we are going to apply AI, and how their job is not going away, it's just going to change. Having that conversation might help get past the emotional part," Krzywosinski offered.

[1] Big Companies Are Embracing Analytics, But Most Still Don't Have a Data-Driven Culture. Davenport & Bean, Harvard Business Review, February 15, 2018.

"Analytics and AI start a conversation," Galindez suggested. "They don't make a decision. AI isn't replacing humans, but it's augmenting humans. We will elevate our work, our jobs, and we will do different things, because we now have the technology that promotes doing things that we previously couldn't."

"But we're challenged with people trying to re-create the future based only on what they know today," Oliver rebutted. "We're giving them new tools, and we're trying to re-boot them, but they're stuck in 'This is the way we've always done this,' instead of standing back and asking whether we need to do it that way in the future. You don't just automate this manual process; you think of a better way to do it. We're trying to retrain people, and we want to give them first shot, but how do you get them over the inertia?"

"We have to be up-front," Sturgill stressed. "There *are* jobs that are going to go away. The machine is going to be doing those jobs. If we start telling people, 'Your job is just going to change,' they will see right through that. If you can't elevate yourself to do a higher-level job, then you're going to struggle. Our job as leaders is to give them the opportunity to re-tool themselves. Not everybody will last."

"The middle management tier is where a lot of these transformation efforts either make or break," Advani observed. "Workers will typically adopt a new technology fairly quickly; middle management is where the challenge lies."

"Part of the problem is that we have optimized and rationalized and pushed those managers into an area where they have no room to get out of it," Meyer pointed out. "Their merit reward isn't based on driving change, it's based on getting their tasks done. They want to change, but they don't know how to, because they can barely do what they're already supposed to do."

"You hired middle managers to optimize for the task," Trajman shrugged. "You didn't hire them with the idea that they would ever have to take on this role. Their management capabilities are over-optimized for this job, and the consequence is that they're not suited or skilled for the next job."

"But some of the folks in middle management don't see the possibilities," Krzywosinski lamented. "In our experience, the millennials are leading middle managers on our digital journey. We are having very candid conversations about expectations and how those are changing.

"Look, the pace of digital change is just ridiculous, and so is the scale," Hinchcliffe interjected.

> Companies give four to five percent of revenue to try to automate and transform the entire organization: all the partner relationships, everything customer interaction. It can't be done. And frankly, we shouldn't.
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> But we *do* need to enlist and empower more people, in more parts of the organization. Overly centralized processes bog down in giant backlogs; centers of excellence models last a little longer, but they bog down, too. The model that works is to enlist change agents from around the organization who have great ideas, and who want to make their

> part of the business better. That gives scale and reach and the ability to tap into people who want to be part of it.

Steve Plume reacted with a perspective based on long participation with the Roundtable:

> I've been with this group for 8 years, and in every one of those 20 or so sessions, someone has said 'Things are changing faster than ever before,'" Plume observed. "I'm hearing more angst today on this topic than I've ever heard before: Is the world hitting a qualitative threshold, where we are really shifting into machine time, and the business cycle is going to accelerate past the human ability to adapt?

"There's an idea of corporate share-of-mind versus what the technology is capable of," Sturgill answered. "What is our organization's ability to absorb change compared to what is the scale of change we're throwing at it? And I believe we're getting very close to the limit of mind share."

"In the past, the critical path has been compute speed, or some other machine limitation. Now it's organizational. I could see a scenario where my organization can be upskilled and move a lot faster, and perhaps match the speeds of the machines of today, if we could re-skill those people and get them fully on-board with the transformational workflows. It's an iterative and evolving process," Krzywosinski said.

Paulonis expressed more uncertainty:

> Most people are inherently capable of soft-skill changes. But the technical aspect of what we're asking people to do here goes beyond giving someone a new system: We're actually trying to get more insight on the problems of the day. We may be able to find the prime movers, the change agents, but what about the rest of the organization, that isn't in those roles? People who need digital skills to succeed in jobs that aren't necessarily digital? Those skills are going to be in very short supply, and I don't know that we're going to be able to re-skill enough of our own people.

"What's more, is that the types of things that start-ups do are often translatable to different industries that may or may not expect them," Brechbühl added. "No start-up can replace a big company, but three different ones can jump out of completely different industries and eat at the edges."

Shurts summarized the concerns about the new world of data and decision-making:

> Most of our companies weren't born digital. Our pasts and our heritages are a big disadvantage in terms of the pace of change that we're talking about. The degree of difficulty to change is a whole lot greater for us than for the greenfield start-ups who are giving many of us a run for our money. Others are out there, doing it faster. The angst is around, "Can we get there fast enough?"

Participant List

Decision Making: Data and AI

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